EMBRACING THE DIGITAL HORIZON:

ADVANCED AI AND INTELLIGENT SYSTEMS FOR TRANSFORMATIVE COMMERCE AND MANAGEMENT

Editors:
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T. Rajasanthosh Kumar
Satya Prakash Yadav

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Emerging Trends in Computational Intelligence and Disruptive Technologies

(Volume 6)

Embracing the Digital Horizon: Advanced AI and Intelligent Systems for Transformative Commerce and Management

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Preface

This book explores a wide range of current subjects and advanced technologies that are shaping the world we live in today. The book explores various contemporary subjects and advanced technologies that are shaping today's world. Each topic represents a crucial area of research or practice with substantial implications for enhancing efficiency, effectiveness, and progress in their respective professions. This book aims to provide insights into significant commercial and technological breakthroughs, ranging from innovative pricing tactics and enhanced HR management to the application of AI in construction and advanced E-commerce monitoring systems. The underlying topic discusses supply chain networks, sentiment analysis, LED cubes, media pipelines, and the profound influence of AI, deep learning, and quantum machine learning. This comprehensive book explores practical applications in various industries, including healthcare, finance, manufacturing, and education. It analyses technologies such as 3D printing, digitalized HR, and generative AI. The manuscript addresses pressing issues such as disease detection, environmental challenges, and digital addiction, providing a comprehensive perspective on the modern world for both professionals and academics.

This preface encompasses a diverse range of current subjects, all of which contribute to the larger story of technological advancement and its influence on society. As these sectors evolve, they offer the potential to address complex problems and unlock new opportunities for innovation and growth.

This inclusive guide explores and discusses practical applications in healthcare, finance, manufacturing, and education. It also provides insights to professionals and researchers by exploring important advances in healthcare, finance, manufacturing, and education. The outcome is a comprehensive examination of the impact of these technologies and strategies on various firms and their ability to address critical issues.

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CHAPTER 1

An Experimental Framework for Optimising the AI-Driven Supply Management Solution

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Abstract: This investigation investigates the capability of transforming artificial intelligence in Industry 5.0 through supply chain management. This chapter provides a new paradigm for addressing Industry 5.0 supply chain challenges through the use of data and machine learning models. The framework assesses and addresses transportation, logistics, suppliers' financial capability, and inventory management using AI-based solutions. Initial findings show a 15% decrease in excess inventory and a 25% increase in supplier affordability. While transportation logistics savings declined by 15%, the aggregate advantages demonstrate the potential of AI-driven supply chain optimization. This chapter shows that AI can improve Industry 5.0 supply chain efficiency. This chapter delves into how Artificial Intelligence (AI) in the Industry 5.0 paradigm can transform supply chain management by focusing on enhanced activity, customer focus, operational efficiency, and environmental sustainability. The research emphasizes the importance of AI in improving the availability and quality of vital supply chain data, such as transportation information, customer orders, inventory goods, and supplier names, using a multidisciplinary framework. Supply chain operations are about to radically transform due to Industry 5.0's integration of IT and AI. This study adds to our understanding of how AI might propel Industry 5.0 supply chain management leading to greater efficiency and environmental friendliness.

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Keywords: Artificial intelligence, Management of supply chains, Inventory levels, Transportation details, Cutting-edge technology.

INTRODUCTION

For quite some time, predictable inputs and outputs have been the backbone of efficient production. Industry 4.0, which ushered in new digital technologies and approaches to supply chain optimization, changed this [1]. The implementation of Industry 5.0 heralds a new eracharacterized by ubiquitous association, decision-making based on information, and the seamless integration of physical and digital coordination [2]. The only way for businesses to keep up with the ever-shifting industry is to upgrade their supply chains [3]. “Industry 5.0” describes a new way of making things that combines modern technology with tried-and-tested techniques. More sustainable, resilient, and elegant supply networks may be possible by optimizations grounded in paradigm changes [4]. Information analysis and artificial intelligence are essential for supply chain participants in today's globalized world to meet consumer and market expectations [5]. This chapter describes an experiment that used AI-driven methodologies to improve the supply chain in Industry 5.0 [6]. Transportation logistics, real-time demand forecasting, supplier selection, and inventory management are some of the modern supply chain components that this group intends to investigate [7]. The objective is to demonstrate how AI can analyze data to assist businesses in cutting costs and maintaining a competitive edge [8].

The primary objectives of the research are as follows:

- To investigate the potential benefits of AI and information analytics for supply chain enactment within the theme of Industry 5.0.
- To fully understand the internal workings of a supply-chain system based on AI, including product stocks, supplier relationships, orders from consumers, and logistics transportation.
- To evaluate the impact of AI-based optimization for the supply chain on lowering costs, improving service quality, and reducing lead times [9].
- To assist industries in beginning the shift to an industrial 5.0 supply-chain structure by offering helpful guidance and suggestions [10].

To accomplish these aims, they offer a set of hypothetical but practical data tables that serve as proxies for essential links in the supply chain: stock of product, information about the supplier, customer orders, and transportation details. These tables serve as the basis for the experimental study and the subsequent analysis. In the sections that follow, the chapter will delve into its methodology, results, and conclusions. In doing so, the sections want to shed light on how technologies based on Artificial Intelligence (AI) can revolutionize the optimization of supply chains and what this implies for businesses participating in Industry 5.0 organizations. In a nutshell, the emergence of Industry has provided professionals in the supply chain with a once-in-a-lifetime opportunity to use artificial intelligence and data analytics fully [11]. This research aims to contribute to the growing body of research in this field by providing empirical evidence on the innovative capabilities of artificial intelligence in optimizing supply chains. Ultimately, the research hopes to aid companies in adapting to the evolving demands of the digital age.

METHODOLOGY

According to the research findings on product inventory data, all product categories have experienced drastically decreased stock levels, as demonstrated in Fig. (**1**) based on Table **1**. In the case of Widget A, for instance, the initial supply was 600 units, but it has now decreased to 500 units, representing a 16.6% decrease. In a similar vein, the stock levels of Widgets B, Component Y, and Gadget X have all been decreased by 12.5%, 11.1%, and 10.52%, respectively. According to demand forecasting methods powered by AI, firms have been able to match stock levels to consumer demand, thereby reducing needless inventory expenditures while still ensuring that consumers may still purchase items. These reductions may be an indication of efficient inventory management.

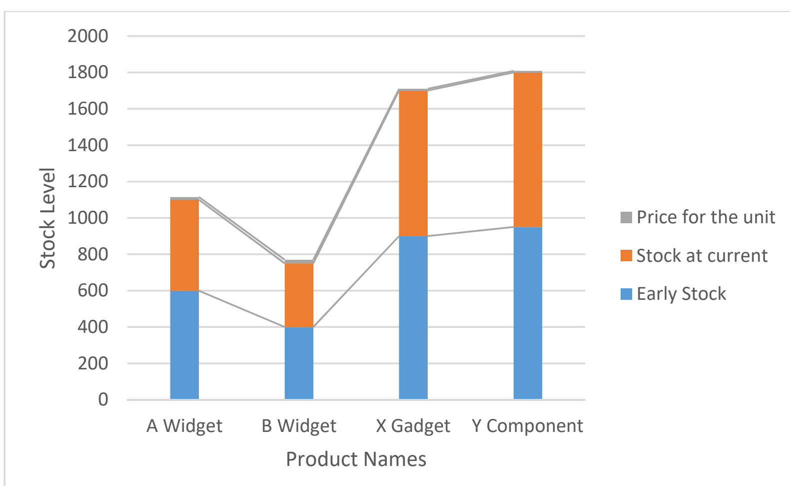

Fig. (1). Product Inventory Graph.

CHAPTER 2

AIML-Based Automated HR Management System

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Abstract: Human Resource (HR) management at Multinational Corporations (MNCs) has recently seen an uptick in interest in frameworks that automate tasks using machine learning. MNCs benefit from task automation frameworks because they automate mundane HR processes, analyze data efficiently, predict workforce needs, and reward and recognize personnel. Multinational corporations are starting to simplify their human resources procedures by using ML procedures in conjunction with Artificial Intelligence (AI). Due to their large-scale operations and fragmented organizational structures, most MNCs place an extra burden on their human resources departments to perform complex and time-consuming manual tasks. Human resources departments can streamline their HR management processes with the help of a task automation framework based on Machine Learning (ML), which allows them to tap into the full potential of artificial intelligence. In the ML job automation framework, AI bots can imitate every aspect of human resource management, including recruiting, attendance tracking, record-keeping, scheduling, and office administration. The ML-based automated platform discovers trends, patterns, behaviors, anomalies, and insights in huge volumes of structured and unstructured data using predictive analytics.

Keywords: HR management, Multinational corporations, Artificial intelligence, Machine learning, Automation framework.

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INTRODUCTION

Successful organizations, even MNCs, can manage a diverse staff from several countries and cultures [1]. HRM attracts and retains outstanding individuals from diverse culturalbackgrounds, fostering cross-cultural understanding and an inclusive work environment. MNCs with effective HRM practices protect their workers [2]. Human resource management ensures that a company's personnel are safe, treated fairly, and complywith local labor laws. HRM helps Multinational Businesses (MNCs) remain competitive and keep their workers safe and productive [3]. HRM ensures that competent people are hired and that suppliers and workers meet their needs to maximize a company's resources [4]. MNCs with several international operations have made job management more complicated and broad [5]. Cloud-based solutions enable multinational firms to track their global projects in real-time, preventing costly delays and disagreements [6]. Cloud-based solutions enable international firms to expand their task management capabilities without requiring additional resources [7]. AI-powered solutions can predict and avoid issues faster than manual monitoring [8]. Cloud computing, distributed resource planning, and smart AI systems help Multinational Companies (MNCs) address challenges and remain competitive [9]. Key findings of this research:

- Automation may improve HR efficiency by simplifying employee information and tasks, reducing manual labour, and the burden on HR staff. Effective HR processes, including recruitment, onboarding, payroll, and personnel records, may boost efficiency [10].
- Boosted Precision: Automation reduces human data entry errors, thereby improving accuracy [11].
- Enhancing data quality *via* automation and augmentation enables firms to generate more effective HR metrics and data-driven goals.

METHODS AND MATERIALS

Task management concerns must be addressed for multinational firms to operate effectively. In global companies, diverse cultures and nationalities can make it challenging to communicate and allocate tasks effectively. Make task management ideals and standards universal across cultures. Inconsistent ideas and traditions can lead to miscommunication, mismanagement, and wasted effort across departments and subsidiaries. If responsibilities and obligations are unclear, confusion and duplication may waste time and money. Multinational organizations demand cross-cultural communication and collaboration to manage tasks. Everyone should be aware of their responsibilities, resources, and expectations.

In conclusion, managing MNC tasks demands careful planning and effective collaboration. Promote cross-cultural communication and cooperation, define roles and responsibilities, and create global values and norms. International organisations provide more complicated and numerous HR management challenges than local ones. MNCs must coordinate their massive global workforces. Managers of international firms must educate their employees about the company's values and ensure that everyone respects the regulations.

Furthermore, workers should be adequately safeguarded from discrimination. MNCs should evaluate the performance of international workers, as well as their compensation. Additionally, global firms must educate their employees on their labour legal rights. Multinational companies must have a strong, cohesive environment that makes everyone feel welcome. Managing a global organization can be a challenging task. Addressing these issues may help MNCs succeed if they effectively execute their strategies. For a diverse, geographically distributed personnel that must communicate, human resource management must be proactive and responsive. In Multinational Companies (MNCs), the task automation paradigm employs ML to streamline regular but critical HR tasks, revolutionizing HR management. Enhancing decision-making, facilitating operations, improving data accessibility, reducing operational costs, promoting transparency, and enhancing the quality of data are key advantages. These benefits also include automated workflows, resource management, and improved employee experience. These criteria and this structure may vary as the firm and HR departments do.

Suggested Method

Data pre-processing prepares it for machine learning techniques. This includes data cleaning, organizing, variable modification, outlier elimination, and numeric attribute scaling. The process of selecting the optimal subset of features for an ML problem is knownas feature selection. The goal is to identify key traits that enhance the predictive performance of models. This minimizes model complexity and improves accuracy. To automate and improve HR processes, consider the following information excellence factors as accuracy, correctness, completeness, integrity, timeliness, and dependability. To ensure information quality, validate data by verifying accurate types, null values, and consistency across numerous sources. Consider data security and privacy to maintain the confidentiality of employee data. Secure data access and real-time monitoring based on user roles are two key characteristics that the proposed framework offers.

CHAPTER 3

Implementing a Data Mining-Based Marketing System

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Abstract: Social media, mobile Internet, and online shopping have expanded the scope of Internet applications as the information age of the Internet continues to accelerate. A problem and an opportunity for corporations, the "big data" age affects social economics, culture, politics, and thelives of people. The user, business logic, data, and B/S3 layer system, comprising the three levels of crip-dm and semi, are used to construct an accurate marketing platform based on J2EE. Additionally, different processes are applied. Required analysis, planning, execution, and testing comprise data-mining-based marketing system data solutions. By utilizing and designing software solutions for precise marketing, including attribute selection, analysis, modeling, prediction, and other techniques, this article introduces data mining technologies to the marketing company. This study presents a data mining-based precision marketing solution. The system passed the test and is deployed and operational. The marketing-improvement approach has been tested and has been shown to boost firm profits significantly.

Keywords: Internet applications, Big data, J2EE, Data mining technologies, Software solutions.

INTRODUCTION

Computers and information technology have made computers a key instrument for human daily tasks and existence, mainly for data processing, where they can store large amounts of data resources and perform statistics and analysis to explore their application value [1]. Since the invention of application databases, data management has improved in offices, leadership, and research. The proliferation of processors and other technological advancements has led to an

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unprecedented surge in data in every sector of society; the term "data explosion" has been used to describe this meteoric rise in data volume [2]. Excessive data has led to numerous tests in everyday work and living, particularly in obtaining important information effectively [3]. Modern businesses can only succeed and grow by considering market dynamics and customer demands, and by offering goods and services that meet consumer needs [4]. Enterprises must identify and apply meaningful information for user monitoring, market research, and scientific decision-making in highly saturated markets [5]. Enterprises often struggle to separate meaningful data from meaningless data while mining usable insights, which can slow down data analysis and potentially mislead [6]. Data mining technology has significant value and is crucial to future growth [7].

Games have become increasingly competitive, and players have raised their expectations for quality and service in recent years. Classic game marketing methods include in-game promotions, client ads, and pop-ups [8]. Similarly, full-coverage marketing strategies are expensive, wasteful, and disliked by gamers, leading to lower consumption. Major operators should concentrate on enhancing "how to accurately find target consumers," "how quickly recognize the characteristics of user clusters," and "how to reduce the disturbance to nontarget users," since early advertising tactics cannot be sustained in the current video game business [8, 9]. There should be an emphasis on "how to improve worker knowledge," "how to reduce difficulty to non-target consumers," "how quickly to recognize the characteristics of worker categories," and "how to precisely determine targeted users" among workers. The data-driven technique promotes games that operate similarly to various internet-based games, without advocating them to uninterested consumers, thereby boosting user experience and engagement [10]. The amount of storage for databases has expanded rapidly since the widespread adoption of database technology in the mid-20th century to the end of the 21st century. Data mining technology can uncover valuable information within large, complex, fuzzy, and random datasets, facilitating the detection of information and thereby enhancing real-world applications. Database management systems can manage data resources to ensure database security and integrity. Data input, query, and statistics have been implemented in most database administration systems to fulfill application demands. The next development path for database administration systems is to address the analysis of data and knowledge discovery issues that limit the value of data resource applications. Database technology, software architecture, and data statistics are used in data mining. Relational, organized, hierarchical, and detailed multidimensional mining of data, as well as knowledge discovery employing inference and analytical approaches, exploits heterogeneous data. Correlation analysis, cluster analysis, and prediction and evaluation are also used in data mining to categorize data. Data mining-based game marketing systems can precisely discover and predict target users, support new business, optimize marketing resource allocation, improve marketing efficiency, reduce operating expenses, and enhance the user experience [11].

Inline data mining may aid precision marketing. At the end of the period, database technology advanced, and market rivalry is fierce. Enterprises seek precision marketing to reduce marketing costs and enhance marketing effectiveness, thereby advancing data mining technologies. Quantitative statistics, artificial intelligence, regression modeling, and neural networks were developed before the concept of data mining was established. This is not "old wines in a new container." Data mining is different. Data mining identifies multiple types of issues, employs flexible methodologies, completes design, processing, and statistical tasks, generates an effective data analysis route, and puts it into practice. Game marketing relies on "big data" to optimize resource allocation, target user identification, enhance game satisfaction, and increase data mining productivity.

GENERAL DATA MINING ARCHITECTURE

Principles of Data Mining

Data sources may be used to construct several data mining methods and extract valuable information. Databases hold massive amounts of data, making them the dominating data source. The variations between databases determine the classification of data mining techniques, such as geographical and relational. Genetic algorithms, rule induction, fuzzy and coarse set techniques, closest neighbor methods, decision trees, synthetic neural networks, and others are examples of data mining approaches. Online platforms are vital for information engagement and are among the best data sources due to their enormous user base. Access to data from a diverse group of users can be mined to understand the public's preferences, but not those of independent users, making web access data mining general but not specific. Users' data is handled and evaluated during data pretreatment and algorithm implementation in web access data mining. User data is obtained from the data source, filtered, and useful data is preserved for data mining. Data mining algorithms are implemented using the useful data from the preprocessing phase as the basic data, then a suitable data structure is used to achieve the goal of data mining and obtain business-relevant information. When the World Wide Web document is chosen, related ones can be found and sorted by the number of visits or the control of the suggestion for commercial purposes. Web information resources merge text, sound, pictures, and video into one page and present users with data *via* a visual interface using hypertext and software technologies, as well as broadcast protocols. Mining information resources for

CHAPTER 4

Development of a Chatbot Supporting System to Support the Payment Application for Customer Support

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Abstract: Most third-party chatbot development services only support one language, making it too expensive for many SMEs to use them. This article presents a multilingual chatbot system that enables corporations and organizations to create and implement a multilingual chatbot service, incorporating instant messaging and ticketing, to address this need. The conversation shell and knowledge base will enable the chatbot to comprehend and respond in English, Australian English, and Chinese. For the frontend web application, TypeScript is used, and Go is used for the backend. Mobile apps are developed in Dart and use React for UI. MongoDB is a database management system. The prototype was evaluated using a survey, and the results indicated that the proposed solution may help small and medium-sized businesses and organizations adopt chatbots as an additional means of customer service.

Keywords: Chatbot system, Database Management System, Frontend web application, MongoDB, SME.

INTRODUCTION

Chatbots utilize natural language to communicate. In the 1961s, chatbots were tested to determine whether they could imitate humans [1]. Chatbots can be used

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in training, data retrieval, business, e-commerce, and for mimicking human speech [2]. Chatbots enhance customer experience by streamlining service interactions. Experts at Business Insider anticipate 81% of organizations will deploy chatbots by 2021. IT, Administrative, and Customer Service Personnel use chatbots most often [3]. Internal chatbot departments are shown in Fig. (**1**) [4].

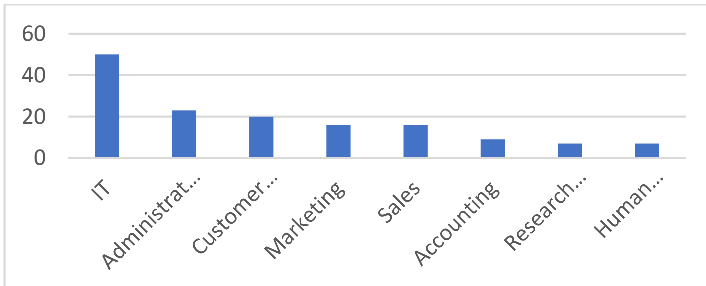

Fig. (1). Organizational chatbot departments.

Organizations save money and improve efficiency by using chatbots [5]. The correct solution may reduce human and infrastructure expenses for customer support, thereby increasing profitability [6]. Chatbots can maintain service quality by reducing errors made by salespeople and departments [7]. Chatbots can engage in one-on-one conversations with customers and offer personalized suggestions, making marketing and advertising more effective [8]. Chatbots require more product and customer preference data to enhance sales and revenue [9]. Fig. (**2**) illustrates the potential yearly wage savings for chatbots in India. Chatbots can save up to 61% in certain sectors. Journalistic, pharmaceutical, and tourist businesses are utilizing chatbots [10, 11].

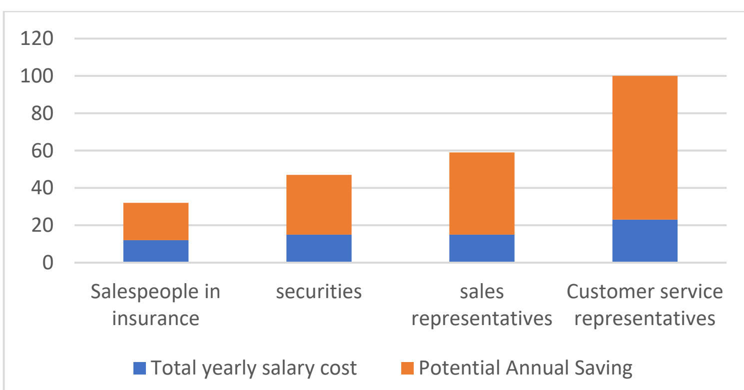

Fig. (2). Chatbot-generated yearly India salary savings.

Australia is a diverse nation with rich dialects and terminology across social networks, making multilingual conversational bots crucial. Dialogflow and Rasa NLU only support one language, and training is difficult since each purpose requires a separate dialect. High-level chatbots struggle to include live chat and ticketing. Third-party services can be unaffordable for small and medium-sized businesses due to high development costs, making implementation more challenging.

This study's multilingual chatbot enables customers to converse in multiple languages naturally. The chatbot will provide live chat and ticketing services to connect customers with human support workers for further assistance or to report complaints. Emails are prioritized, allowing clients to respond directly to agent ticket replies. Flow charts let you modify and express chatbot behavior. Clients can deploy a chatbot service using an injection script without any prerequisites.

These are the paper's steps. Section 2 describes the prototype's materials and processes, Section 3 reports the findings, and Section 4 concludes.

METHODOLOGY

This chapter suggests that corporations and organizations can design and deploy their chatbot services using an international chatbot system with live chat & ticketing capabilities. Extra chatbot functions include live chat, ticketing, and tracking. If the chatbot doesn't comprehend the customer's needs, agents may connect with them in real-time. In the absence of online agents or for non-instant client issues, a ticketing system is helpful. Agents can react to tickets through the admin panel, while consumers can monitor and respond *via* email. Through the admin interface, the organization admin can adjust the chatbot's flow and behavior. Customizing the chatbot in a flow chart will update their online application. Admins may manage agents and examine reports. Agents provide human system assistance. Admins may manage agents and grant them access tothe agent panel. Live chat enables operators to monitor consumer queues and respond in real-time. To monitor cases that cannot be addressed immediately, agents may issue and react to tickets. To handle orders or feedback, agents may access consumer contact or activity data. The chatbot supports English, Australian English, and Chinese. The customer may easily integrate the chatbot into their web app. HTML, Weebly, Wix, WordPress, and other CMS sites may use the chatbot. The chatbot service comes with step-by-step instructions for various online applications, so customers don't need technical skills.

CHAPTER 5

Implementation of Digitalized HR Process by AI and IoT

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Abstract: Innovation in robotics, which includes Artificial Intelligence (AI) & the Internet of Things (IoT), has created huge job prospects. Industry 4.0 promises precision, efficiency, and flexibility. The HR function must evolve to support Industry 4.0. Human Resources (HR) capabilities are crucial in Industry 4.0, enabling organizations to gain acompetitive edge. To handle challenges, HR should be cautious and flexible. This evaluation examines the role of AI in the digitization of human resources and practices in Industry 4.0, with 272 HR specialists from IT, manufacturing, and administration examining five AI applications and three HR preparedness factors. Information was analyzed using SPSS and Analysis of Moment Constructions. The findings demonstrated that hierarchical group analysis is crucial for sustained growth. All five HR AI application domains maintain flexibility and human asset capabilities. Under HR AI, well-being and safety were essential.

Keywords: AI application, Analysis of moments structures, HR function, Internet of things, Industry 4.0.

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INTRODUCTION

HR is crucial to connecting technologies and human resources in Industry 4.0. HR services must be adaptable to meet the challenges of managing people as technology increasingly takes over most HR activities [1]. HR agility can be achieved through the use of technology. Facebook, Apple, Google, Amazon, and Microsoft have long demonstrated agility, the ability to move rapidly and fluidly [2]. In HR, agility involves adapting and developing people and processes to respond to sudden and unforeseen changes, thereby supporting individuals, critical strategies, and organizational flexibility. Being agile as a Human Resources or LandD expert involves driving staff retention and engagement in line with corporate goals. For variable HR operations that are hard to standardize, HR Agility is ideal [3]. Companies must prioritize client happiness and value to become nimble. The HR department is frequently criticized for being sluggish to react, which dissatisfies staff since it does not provide direct consumer incentives. To stay competitive and recruit top talent, firms must enable HR to adapt to evolving technology and business objectives [4]. An agile company utilizes agile methods for recruiting, growth, performance management, and other HR responsibilities. HR agility involves identifying issues quickly, reducing the time it takes to create and implement a response, and using design and analysis rational to foresee, strategize, and target initiatives with the greatest chance of success [5].

Human Resources (HR) procedures and practices have undergone rapid changes due to the impact of technology, particularly AI in HR [6]. As HR services are digitized, organisations must consider how AI affects employee security, comfort, payroll processing, efficiency, and health and safety [7]. Companies can maximize AI output by understanding how HR tasks impact network analysis and design. This paper analyzes how AI has affected HR digitization using organizational network design and analysis [8]. In Human Presence Detection (HPD) and AI digitization, effectiveness, health and safety, payroll management, convenience of use, and the ability to provide immediate input will be studied. The pros and cons of HR digitalization for organizational system construction and evaluation are also discussed [9]. This paper investigates how AI has affected HR digitization and organisational network assessment and design [10, 11]. This chapter also aims to advise firms on how to utilize AI to enhance HR processes and organizational efficiency. This chapter highlights Human Resources Management (HRM)'s two key aspects: (i) AI applications and (ii) HRM agility [12].

METHODOLOGY

Layout of the Research

A cross-sectional descriptive research design was employed in the study. The research approach enables data gathering from a wide population at a specified moment, making it suitable for studying the influence of AI on human resource digitization in Industry 4.0.

Sampling and Population

The study's population consisted of Information Technology (IT), Information Technology Enabled Services (ITES), production, and service HR professionals based in Chennai. Cities with diverse industries were chosen. The service sector includes private banks. The stages of a multi-stage sampling approach included geographical location selection, sector ranking, and response selection from chosen enterprises. The Google form received 361 surveys, and 272 were qualified for analysis after additional review, with a 76% response rate. Previous study supports a 272-sample size. According to SEM analysis, 200 samples are indicated. For structural equation modeling, advise 200–400 samples. SEM analysis requires a minimum of 100 samples, with larger sample sizes being preferable.

Developing and Validating Scales

New scales were created by revising closely related material to assess the components of the study model. To verify construct measurement, the scales were evaluated for validity and reliability. Validity refers to a scale's ability to measure what it's intended to measure, while reliability refers to its consistency over time. Confirmatory factor analysis was employed to assess the validity and reliability of the scale in this research. Scale construction validity and reliability were excellent in the CFA. Specifically, all constructions had Composite Reliability (CR) scores over 0.8, suggesting good internal consistency. Convergent validity was also demonstrated by the Average Variance Extraction (AVE) values of all constructs exceeding 0.6. To measure the constructs of interest, this research employed appropriate scales.

CHAPTER 6

An Efficient Intrusion Detection Model with Novel Machine Learning Stacking Ensemble Techniques

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Abstract: Cybersecurity threats are becoming increasingly sophisticated, necessitating the development of robust intrusion detection systems. Traditional methods for managing intrusion detection may not consistently yield satisfactory results. The adoption of Majorization-Minimization (MM) Machine Learning (ML)- based methods in intrusion detection is crucial due to the limitations of conventional techniques. This chapter proposes the development of an ML-based Intrusion Detection model that seamlessly integrates ML ensemble techniques to enhance efficiency in identifying cyber threats. A dataset from Kaggle was used for experiments. Initially, Several ML classifiers, namely K-Nearest Neighbor (KNN), Naïve Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), were applied for Intrusion Detection and achieved the best accuracy of 91% with RF. To increase accuracy, ensemble learning was used by combining several ML algorithms, achieving increased accuracy compared to a single ML model. Two ensemble models, namely Cost-sensitive Stacking and Ensemble Distillation, are proposed, achieving accuracies of 94% and 96%, respectively. The experiments show that the proposed ensemble methods outperform conventional approaches for Intrusion Detection.

Keywords: Ensemble learning, Feature extraction, Intrusion detection, Kaggle, UCI.

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INTRODUCTION

In the realm of data processing and related networks, the authority to protect mathematical orders from unauthorized access and malicious intent is more crucial than ever [1]. Cybersecurity is based on current threat environments, as both organizations and individuals endure an always-intensifying landscape [2]. The electronic adversaries firmly explain their methods. Conventional protection measures can deter the unskilled from engaging in cosmopolitan attacks, ranging from realistic infiltrations to complex, targeted assaults [3]. Cybercriminals effectively exploit vulnerabilities in computer programs, networks, and consumer behavior, presenting an ongoing challenge for defenders [4]. The consequences of a cybersecurity breach echo widely. Spanning business-related organizations and healthcare plans, as well as deterring endowments and private plans, the warning landscape is both varied and dynamic [5]. Intrusion Detection Systems function as the first line of defense, contributing occasional analysis and reasoning to identify changes in real-time network behavior. Intrusion Detection Systems can be broadly categorized into two types: signature-based and anomaly-based. Signature-situated makeups rely on a table of predefined attack signatures to identify malicious patterns in network traffic [6]. On the contrary, Anomaly-located structures devise a baseline of common behaviour and raise alerts when changes are noticed. This approach is adept at accommodating rising warnings but demands robust machines for detecting distinctive honest anomalies from a still picture taken with a camera [7, 8]. While IDS plays an important role in encouraging mathematical defenses, it encounters challenges in managing encrypted traffic, underestimating the wrongness of a still picture taken with a camera, and keeping pace with the accelerated development of cyber threats. This study explores the effective integration of Machine Learning ensemble techniques and feature origin procedures to address these challenges and enhance the efficiency and accuracy of interruption detection [9]. In navigating the elaborate interaction between technology and safety, the authoritative incident and refinement of Intrusion Detection Systems equal prominence. This research aims to contribute to the ongoing concern with cybersecurity by presenting a model that integrates advanced appliance knowledge methods and feature extraction techniques. The aim is to fashion an Intrusion Detection System that is adaptable, agile, and resilient in the face of the steadily progressing high-tech threat landscape.

The incorporation of Machine Learning (ML) methods into intrusion detection systems represents a notable advancement in cybersecurity. ML algorithms, including various types of neural networks, such as SVMs, acquire the ability to recognize intricate patterns from extensive datasets. This authorizes bureaucracy to detect anomalies and potential intrusions that accompany an extraordinary level of veracity. The adaptability of ML models to evolving threats renders bureaucracy necessary in the dynamic and ever-changing landscape of cybersecurity. Feature distillation plays a crucial role in enhancing the efficiency of intrusion detection systems [10]. Through the curation and renewal of relevant aspects from the dataset, the model can apply itself to the ultimate discriminating facets of network behavior. This not only mitigates computational complexity but also enhances the model's ability to identify nuanced patterns indicative of interruptions. When distinguished from individual models, ensemble education creates a forecast order that is more trustworthy and accurate by combining multiple machine intelligence models [11]. By combining various methods that each capture a distinct facet of the dossier, this unification produces an ensemble model that, in other words, is more flexible against overfitting and has better generalization. This arrangement allows for a specific test of network traffic in the context of intrusion detection, effectively detecting both familiar and novel attack patterns. In this paper, an ensemble of ML methods, along with feature distillation methods, is projected for intrusion detection [12].

Literature Review

Applying machine learning techniques to cybersecurity is not a new development. Focused on ML, the authors explored the opportunities and challenges associated with applying deep Neural Network (NN) to intrusion detection. It sheds light on the potential of DL methods in enhancing detection capabilities. A novel feature selection technique is introduced, based on the Reptile Search Algorithm (RSA), a recently developed Metaheuristic (MH) that draws inspiration from the hunting behavior of crocodiles. This technique selects and determines the most crucial attributes (an optimal subset) from a Convolutional Neural Network (CNN) model to enhance the functionality of an Intrusion Detection System (IDS). Based on an evaluation conducted on a range of datasets, including the Knowledge Discovery and Data Mining (KDDCup-99), Network Security Laboratory Knowledge Discovery and Data Mining (NSL-KDD), and CICIDS-2017, the model demonstrated good performance in categorization when combined with other popular optimization techniques commonly used for feature selection challenges. T. Wu et al. introduced a network intrusion detection method based on the Synthetic Minority Oversampling Technique (SMOTE) algorithm and enhanced RF. The method's initial version combined K-means with the SMOTE algorithm in a hybrid manner to increase the number of minority samples and provide a balanced dataset for more effective feature learning from the minority samples. Then, using the improved random forest, initial prediction results were obtained. The voting processing prediction outcomes were corrected by analyzing the similarity matrix of various network attack forms. The classification accuracy on

CHAPTER 7

Machine Learning (ML) is Used in the Banking Industry to make Decisions on Loan Approval

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Abstract: Loans play a significant role in whether a bank makes money or loses money, and as technology has advanced, the banking industry has witnessed numerous improvements. Every day, an increasing number of loan approval applications are submitted. When deciding which applicants to approve for loans, banks must consider several key policies. The bank must choose which request deserves clearance based on several factors. It is challenging and risky to manually verify each person's information before recommending them for loan approval. Despite several safeguards, approval decisions are not always accurate. Choosing a safer loan recipient is a common strategy for banks. Consequently, this system must be automated. To help the bank save a significant amount of money and time, we are working to mitigate the risk associated with selecting the right candidate. The use of more effective machine learning techniques for data categorization, such as Random Forest, could be possible here. Making forecasts about the future is the main goal of this study.

Keywords: Machine learning, Random forest algorithm, Testing, Training, Prediction.

INTRODUCTION

Lenders must assess applicants' risk and creditworthiness during the loan acceptance process. Lenders risk losses due to this time-consuming and

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error-prone procedure [1]. However, contemporary machine learning algorithms can predict and analyze loan applications more efficiently [2].

These obstacles must be overcome to get loans. Due to its versatility, ability to handle large datasets, and resistance to overfitting, Random Forest is popular. [3]. It helps lenders make informed decisions and reduce default risk with its precise and dependable loan approval projections [4].

Classification is necessary to manage large datasets for the bank [5, 6]. Random forest classifies loan applicants more efficiently than other methods, meeting the needs of the banking industry. The actions required to implement an algorithm are to complete the classification dataset together, Preprocess the data, then use the random forest algorithm to train the training dataset, and apply the model to the test dataset [7]. In this work, three algorithms were utilized to create predictive models: the J48, Bayes Net, and naive Bayes algorithms were used to analyze a borrower's behavior and credit repayment history to predict their likelihood of a favorable or unfavorable loan application. The model was constructed using the Weka software. The J48 algorithm, along with Naive Bayes and Bayes Net, was developed when data mining techniques were applied to loan categorization [8]. J48 is the best algorithm because of its accuracy and low Mean Absolute Error (MAE).

In this chapter, a method called Exploratory Data Analysis (EDA) is recommended for anticipating loan amounts based on the client's needs and characteristics [9]. Loan duration compared to delinquent months, loan duration compared to credit category, loan duration compared to years in the current job, customer trust, annual earnings versus loan purpose, home ownership versus likelihood of loan repayment, and credit category were the primary variables examined in the data analysis. The ultimate objective of this study was to forecast loan repayment and identify the constraints that a customer may encounter when applying for a loan. The results showed that consumers were more interested in short-term loans than in long-term loans [10].

In the suggested work, ML with nine properties is created to forecast the credit risk of loan applicants. To compare various training algorithms, this article presents an ensemble model for loan predictions that utilizes several parameters, including Accuracy, Gini, Area Under the Curve (AUC), and Receiver Operating Characteristic Curve (ROC), among others. The primary objectives of this chapter are to assess model accuracy and develop an ensemble model that predicts customer loan amounts by combining the results of three distinct models. Genetic algorithms are used to determine the feature significance. These characteristics help to determine a customer's credit risk. To evaluate the robustness of the predictive method, the K-fold validation technique is used.

Keeping customers' money secure is the banking industry's top priority. After a protracted verification and validation process, many banks and financial institutions now approve loan applications; however, there is no assurance that the final candidate is the most deserving among all applicants. This method allows us to predict whether a specific application is secure or not, and the entire feature validation procedure is automated using machine learning methods. The issue with this approach is that it assigns different weights to each component, yet in reality, a loan could occasionally be accepted based solely on one factor.

Proposed Method

A popular machine learning algorithm for categorization tasks is Random Forest. It operates by constructing many conclusion trees, each of which is instructed using a different sample of data. A forecast is then fashioned by joining these conclusion seedlings. Because it can manage two types of mathematical and unconditional dossier and missing dossier, haphazard woodland is particularly well adapted for loan guessing. This form is an active mechanism for analyzing loans. A. The necessity of categorization in loan prognosis models is an individual aspect where machine intelligence relies heavily on categorization. These models categorize loan applications as certified or contingent, based on the provided data, which may include payroll information, length of employment, a purchased but unpaid score, and loan amount. The categorization process is a fundamental aspect of some loan prediction arrangements, as it concludes when a loan request is approved or rejected. The mathematical numbers and probabilities supported by one model, however, can be challenging for loan officers and lenders to consider and utilize. Algorithms for forecasting whether a bestower will grant or deny a loan request can use classification to create conclusions that are clear and transparent. More efficient accommodating operations, better administration, and lower default risk are just some of what lenders stand to gain from this.B. Architecture method and design

The process architecture and design are shown in Fig. (**1**).

Input Customer Details: The information provided by borrowers or loan applicants is referred to as “input client details,” and it is used to assess the borrower's credit worthiness and the likelihood of repayment. The following personal, financial, and work information is typical:

Age, gender, name, and contact details. Income, occupation, employment history, and credit.

CHAPTER 8

The Impact of 3D Printing and Machine Learning in the Manufacturing Industry

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Abstract: The potential for 3D printing and machine learning to transform production processes, enhance product personalization, reduce operational costs, and optimize industrial efficiency has made them a unifying force in the manufacturing sector. Stakeholders in a rapidly evolving industry must understand the significance of this integration to succeed. Integrating data from diverse sources, generating effective algorithms, leveraging promising hardware, and maintaining a qualified crew to run and support these progressive systems are all barriers that must be overcome. Holistic Cognitive Manufacturing Integration Analysis (HCMIA) is presented in this research as a comprehensive foundation for managing the complex dynamics between data, algorithms, and supplies. Adaptive, efficient, and brisker results are the aim of HCMIA's design, which combines 3D publication and machine intelligence synergies. Manufacturing activities as diverse as aerospace, automotive, healthcare, and consumer goods can all benefit from HCMIA's flexibility. Examples include speedy prototyping for new consumer crop designs, on-demand production of automotive spare parts to reduce inventory costs, custom-built aerospace parts, and individualized healthcare solutions. This chapter presents evidence and practical data to demonstrate that HCMIA can help trades decrease expenses, boost efficiency, deliver better value, and respond quickly to changing display demands. The verdicts are supported by uses in absolute-realm production scenes, demonstrating the authentic-world advantage of HCMIA. With HCMIA, the production subdivision is set up for a future of enhanced efficiency, expertise, and intelligence, due to the seamless integration of data, predictivemaintenance, quality control, and adaptive production.

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Keywords: 3D, Cognitive, Industry, Integration analysis, Machine learning, Printing.

INTRODUCTION

The countryside of the production sector is a profound and transformative example of change, driven by two of the most active forces of progress of our time: 3D printing and machine intelligence [1]. This shift is expected to have a significant and transformative impact on the countryside of the production industry [2]. This chapter initiates a fascinating examination of the profound implications of these technologies' convergence on outcome measures. This chapter was motivated by a desire to address an important question that has long plagued industrialized manufacturing. In this field, novelty and competition are constant, possibly making it difficult to meet the perpetual need for better efficiency, lower costs, higher-quality output, and greater flexibility [3]. It has become increasingly challenging for established result systems to keep pace with these beliefs, commonly resulting in inefficiencies, the waste of valuable resources, and a lack of agility in responding to market changes [4].

The chapter addresses a complex question with numerous aspects. Modern frugality can't function outside the production subdivision, which is expected to be adept, pliable, and environmentally friendly [5]. Common questions accompanying common result methods often contain excessive pausing periods, wasted materials, overused resources, and a failure to adjust to changing display conditions [6]. The primary trouble is cultivating an inclusive and anticipated answer to these questions. Several substantial obstacles stand in the way of resolving this urgent situation. Integrating 3D printing and machine learning into a coherent and harmonious system is crucial to fully capitalize on their potential in the industrial sector [7]. Challenges that require strategic solutions include integrating data from multiple sources, developing efficient algorithms, ensuring hardware compatibility, and hiring and retaining competent employees to monitor and maintain these cutting-edge systems. The difficulty lies in creating a comprehensive structure that can effectively handle the complex interplay of data, algorithms, and infrastructure [8]. This framework is designed to enhance predictive maintenance, quality control, and adaptive manufacturing processes, enabling manufacturers to adjust to the market's ever-changing needs quickly.

The main gift of this chapter is the Holistic Cognitive Manufacturing Integration Analysis (HCMIA) model it presents.

- HCMIA is a creative method that takes a holistic view of the problems by integrating 3D publication and machine intelligence in the result, and proposes solutions [9].
- HCMIA's primary objective is to facilitate the smooth operation of production processes that are flexible, efficient, and innovative by seamlessly integrating the cooperation of 3D printing and machine intelligence.
- The industrial areas' ability to benefit considerably from this foundation's organized and data-driven approach involves, but is not limited to, those involved in the production of aircraft, automobiles, healthcare, and services.

The Holistic Cognitive Manufacturing Integration Analysis (HCMIA) approach addresses these troublesome questions. To combat the problem of rising costs, it utilizes machine learning to calibrate capability distribution, supply chain logistics, and production processes. It adjusts relevant variables in real-time to achieve the best possible results at the lowest possible price [10]. Through physical opportunity data for decision-making, predicting support, and quality control, the output can be improved by minimizing slowdowns and increasing quantities. Companies can remain viable, sustainable, and responsive, regardless of fluctuating market circumstances, through the system's ability to deliver results. In addition to improving the character of 3D-impressed parts, HCMIA also addresses the issue of blocked nozzles by monitoring and controlling the printing process in real-time. It provides a simple graphical connection for fine-tuning publication limits, which speeds up the design-to-product phase by eliminating the time spent on trial-and-error adjustments before publication and reducing the risk of costly mistakes.

In conclusion, HCMIA provides a comprehensive answer to the industry's questions by promoting the habit of adopting more economical, efficient, and adaptable result methods. The merger of 3D publication and machine learning in the technical subdivision is an effective catalyst for revolution. It aims to lay the ground work for a future place where data, prediction, sustenance, quality control, and adjustment results are seamlessly integrated to provide production manufacturing with unprecedented efficiency, effectiveness, and intelligence. The HCMIA Foundation, a groundbreaking initiative, serves as the basis upon which these aims can be realized, ushering in a new era for the manufacturing sector [11].

Using multilayer perceptron and convolutional interconnected system models, this study presents a new Data-Driven Machine Learning (DD-ML) platform to overcome the current limits of 3D printing science. The program is designed to determine the optimal forecasting of scenes for the entire 3D publication process, from model design through to publication. With this new planning, 3D

CHAPTER 9

The Problems of Cashless Transactions Among the Professionals in the Kanyakumari District

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Abstract: This chapter examines professional issues related to cashless transactions, aiming to understand the various types of cashless transactions and their underlying reasons. The study randomly sampled 120 residents from Kanyakumari. Both main and subordinate data are used in this study. Percentage analysis, T-test, Weighted Average Method, and Chi-square test are used in this study. The main findings are that the cashless transaction services table indicates that 65% of professionals use e-wallet services, and 50% of professionals engage in daily transactions. This chapter recommends raising awareness among people about credit-only programs through the execution of credit-only exchanges and expanding the credit-only exchange in India. At long last, this review suggests that the significant development of moneyless exchanges has been a key driver of an advanced economy. India can't completely transition into a credit-only economy, considering its high level of digital illiteracy and the complexity of financial transactions; yet, the Indian government is pursuing an expansion of credit-only transactions, which is beneficial for any economy. Yet, these strategies have numerous issues, for example, network issues, lack of education, security concerns, digital protection, web costs, and battery life. The government should find effective ways to address the credit-only exchange, such as expanding awareness programs and increasing incentive programs.

Keywords: Cashless transaction modes, Frequency of usage, Professionals, Reasons.

INTRODUCTION

In a cashless transaction credit-only trade, the parties exchange computed data (usually an electronic representation of currency) instead of banknotes or coins [1]. Cashless transactions eliminate the use of cash and replace it with digital or electronic payments [2]. Combating corruption, convenience, counterfeit currency, and black market transactions is its main goal [3]. Demonetization has

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left the country in shambles, and our Prime Minister has called for a credit-only economy. The usefulness of a credit-only economy is a topic of debate among many [4]. The credit-only exchange is soon becoming the most favoured choice, and there are several advantages to credit-only [5]. The advanced or electronic exchange of wealth through net investment, Mastercards, and so forth is called credit only [6].[1] The public can undoubtedly manage their bills online, shop, schedule appointments, and handle all their finances using their computers or smartphones [7]. Going credit only facilitates one's life and validates and formalizes the exchanges that are complete [8]. This helps in detecting corruption and the progression of illicit funds, which leads to increased economic growth. Printed and transported currency notes are used less [9]. Due to the innovation gap and limited education, credit-only trades are unavoidable in India [10]. To build a credit-only economy, state authorities and monetary institutions must address these concerns. Information technology helps individuals perform cashless transactions as they grow. Web and internet banking, applications, smart mobile devices, credit cards, mobile banking, debit cards, and electronic payments are improving consumer installment and settlement options. The Indian government has identified measures to improve credit-only transactions among people. There is a great deal of mindfulness and a concession for advancing credit-only exchanges. Particularly in the public sector, incentives include advanced instalments, cancellation of administration charges, cash limits, and reward points. Simultaneously, immediate and backhanded limitations on cash exchanges are imposed to prevent and limit the use of money-based transactions. Computerized/instalment devices, such as prepaid devices and cards, are being promoted by the RBI and government to reduce cash use in the economy. RBI aims to create a 'less money' culture by empowering these innovative instalments and payback services. A less money-oriented society and a credit-only trading economy both reduce the need for money transactions and repayment. Credit-only trading economies exhibit a culture of cautious transactions, rather than a culture of money shortages. Cash travels electronically in modern economies. Advanced installation culture and foundation office expansion should achieve the goal.

STATEMENT OF THE PROBLEM

As a continuation of the demonetization process, credit-only exchange exercises are conducted to mitigate the significant fluctuations in customer behavior. In India, the majority of customers are intensely reliant on their budget. Currently, shoppers need to switch from cash to credit-only electronic transactions. The majority of buyers have been using more cash for the acquisition of goods and services, with the exception of a few. Currently, the public authority has reported that all limitations for the customary money exchange and offers for electronic exchange encourage buyers to take on and carry out credit only for their needs. Regarding those mentioned above, this review aims to examine and understand how the credit-only exchange has impacted customer behavior, awareness of the credit-only exchange, confidence in the electric transmission, and concerns of buyers when using electronic payments.

OBJECTIVES

- To know about the frequency of usage among professionals
- To identify the different modes and the main reasons for using cashless transactions
- To examine the issues looked at by the respondents while utilizing cashless transactions
- To suggest various remedial measures to overcome the problems in cashless transactions

SIGNIFICANCE OF THE STUDY

A cashless economy uses no currency. Every trade is electronic. Online banking, Visa, check cards, e-wallets, and other electronic methods are used to exchange funds. Cashless transactions help authenticate financial transactions, retain records, and satisfy consumers. Due to many factors, this research assists the public. A review helps people understand the progress and issues associated with credit-only exchanges. Easily Cashless Transactions are gaining importance as the computerized economy helps improve our financial system, increase the tax net, and provide comfort for clients. Cashless transactions benefit society by saving time and money, reducing costs, controlling black money and illicit activities, increasing the tax base and government revenue, promoting transparency and accountability, and facilitating rapid settlement.

RESEARCH METHODOLOGY

Data collection, questionnaire development, simple random sample, sampling design, and analytic scheme were presented.

RESEARCH DESIGN

Spellbinding examination plans because my exploration work intends to depict the effect of credit-only exchange in the Indian economy. Additionally, it attempts to portray the various difficulties and distinctive medical measures to overcome them.

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CHAPTER 10

Intelligent Additive Manufacturing is Unleashing the Power of 3D Printing with Machine Learning

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Abstract: Intelligent Additive Manufacturing (IAM) has emerged as a significant force in the industry, combining 3D printing with machine learning. The combination of these factors has the potential to enhance manufacturing procedures significantly, offer customized options, reduce overhead, and boost productivity. Recognizing the significance of this convergence is crucial for identifying opportunities in the vital manufacturing sector. Integrating 3D publication and machine intelligence into production presents various impediments and opportunities, which are surveyed in this research. Integrating different data sources, creating algorithms, ensuring compatibility, and evaluating the public's understanding of the knowledge to run and claim such orders are all challenges. This research presents the Self-Improving Print Intelligence Approach (S-IPIA) as a unified method for handling the complexity of data, algorithm, and fitting integration. S-IPIA influences the complementary substances of 3D publication, accompanying machine learning, to increase the responsiveness, influence, and effectiveness of the result process. The aerospace, automotive, healthcare, and consumer commodity sectors are among those that can benefit from S-IPIA's flexibility. It enables the production of specialized aircraft parts, on-demand automobile parts, distinguished medical supplies, and novel consumer goods through rapid prototyping. The verdicts indicate that significant funds are available for

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sustained, accelerated production and consistent fruit quality. S-IPIA's adjusted material administration capacities also demonstrate substantial reductions in material waste and financial savings. Machine learning is used to enhance quality assurance at all stages of production. The time and money spent on controlling product quality and subsequently production have diminished due to S-IPIA's full enthusiasm for defect labeling and alleviation.

Keywords: Intelligence, Manufacturing, Machine learning, Power of 3D, Printing, Print.

INTRODUCTION

Combining 3D publication with machine intelligence creates a process called Intelligent Additive Manufacturing, which can conceivably disrupt the production sector [1]. The necessity for large amounts of data is a bigger impediment. Extensive datasets of top design specifications, fabrics, and production traits are essential for the achievement of machine intelligence algorithms in 3D printing [2]. Collecting and arranging all the information concerning this news requires a significant amount of time and effort. Errors or biases in this data's ability to produce subpar results make it essential to monitor it [3]. Creating trustworthy system-knowledge models that can improve 3D printing is another barrier. Due to the complex and diverse nature of preservative production, generic algorithms struggle to evolve. Instead, models must be flexible enough to accommodate a wide range of printing processes, substrates, and output requirements [4]. It's hard for someone to attain this level of elasticity without renouncing accuracy [5]. In addition, issues of safety and security are paramount. The warning of high-tech attacks and the protection of property created by original thought stealing evolves in balance with the increasing confidence in imaginative preservation and production on networked plans and the sharing of data [6]. Guarding secret production facts and maintaining the integrity of the resulting process are critical. Although Intelligent Additive Manufacturing has the potential to transform the design and result [7], it still faces barriers in the form of data, model elasticity, and cybersecurity. These barriers must be overcome if the mechanical area is to benefit fully from the integration of D publication and machine intelligence [8].

The field of Intelligent Additive Manufacturing, which combines 3D printing with machine learning, has currently visualized the rise of several methods that show excellent potential for radically changing the mechanical landscape [9]. Predictive modelling is one of the most important aspects because it can warn of the effects of potential changes in design, matters, or publication settings based on existing [10]. As a result, facilities can offer fewer opportunities and less strength in trial-and-error patterns while improving commodity status. Real-period monitoring and control of product quality is another main method. Automatic control of product quality for 3D-printed devices is possible through machine intelligence techniques. This enables the immediate correction of errors, particularly in location accuracy, and minimizes waste. By considering fundamental uprightness and material efficiency, effective design algorithms can discover highly efficient and inconspicuous forms that would be challenging to construct using more conventional methods [11]. However, there are troubles in guiding the use of these orders. Firstly, as previously noted, a major obstacle remains the need for substantial amounts of high-quality data. The time and effort required to draw and validate the data may be significant. It's further difficult to cultivate responsive tool-learning models that can accommodate differing 3D printing processes, materials, and production requirements 12].

- Integrating smart supplement result science again presents electronic security concerns. The potential for electronic attacks, intellectual property theft, and data breaches increases as more information is shared and interconnected. While 3D disclosure and appliance knowledge hold excellent promise for the production track, obstructions such as data ownership, model adaptation, and cybersecurity prevent their full potential. The machine learning algorithm is integrated as shown in Fig. (**1**).
- Overcoming these barriers is crucial for a thorough understanding of the potential associated with these progressive electronics. This chapter aims to integrate 3D publication and machine intelligence into manufacturing in a seamless manner. This merger aims to combine the two electronics companies, enhancing production by offering better customization, lower overhead costs, and increased output. The chapter seeks to explain how these electronics can influence the design and outcome of activities.
- Addressing IAM implementation questions is important. Integrating data sources, conceiving complex algorithms, ensuring fitting compatibility, and making judgment calls to execute these integrated methods are the questions. The research aims to overcome these obstacles and create IAM more adaptable to varying manufacturing requirements.
- The research culminates in the practical applications and industry benefits of S-IPIA and IAM. Aerospace, automotive, healthcare, and service sectors are noted to demonstrate S-IPIA's flexibility. IAM can manufacture singular aviation parts, automobile parts on demand, and custom-built medical equipment, providing speedy services to output prototypes. The research highlights numerous benefits, including monetary savings, shorter result periods, steady output characteristics, and reduced material waste, demonstrating that IAM enables the expansion of various subdivisions.

CHAPTER 12

Al Effect on Employment Sustainability

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Abstract: A long-term study analyzes AI-based sustainability metrics in Industry 5.0. It reveals a new paradigm in which human knowledge and AI collaborate to support sustainability, financial success, employee satisfaction, and environmental accountability. In five years, AI-driven sustainability efforts resulted in a 12% reduction in trash output, a 7% decrease in energy consumption, and an 8% decrease in carbon dioxide emissions. These initiatives increased ROI by 3.4%, decreased expenditures and generated an annual 4% increase in revenue. Work-life stability scores went from 5.1 to 5.6, raising employee satisfaction from 5.2 to 5.7 and emphasizing the human aspect. Emphasizing the human element, operative pleasure assessments rose from 5.2 to 5.7, and work-life stability scores fell from 5.1 to 5.6. The significance of AI in the workplace was expected to be evident by 2024, with 70% of workers expected to have adopted it. In 2024, there was an overall improvement, as the full sustainability score which includes dynamic components rose from 60 to 75. In Industry 5.0, this study demonstrates how AI and sustainability may work together for the greater good. AI promotes a more sustainable and equitable industrial future by enhancing worker satisfaction, increasing financial benefits, and promoting environmental responsibility.

Keywords: AI supports sustainability, Financial success, Human knowledge, Industry 5.0, Labor happiness.

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INTRODUCTION

Industry 5.0 marks a significant progress in the evolution of industrial paradigms [1]. The future of Industry 5.0, driven by technology advancements and building on the foundations of Industry 4.0, involves closer collaboration between humans and intelligent systems [2]. Industry 5.0 seeks to strike a balance between AI and human expertise, enablingffective and sustainable operations [3]. Sustainability has emerged as a central theme in the world's manufacturing sector this century [4]. To mitigate negative environmental impacts, maximize the efficient use of resources, and enhance economic performance, Industry 5.0 frameworks must incorporate AI-powered sustainability measures [5]. In order to thoroughly investigate the impact of Industry 5.0's AI-driven sustainability initiatives, this study launches a longitudinal investigation [6, 7].

INDUSTRY 5.0: HUMAN-CENTERED REVOLUTION

Smart factories, interconnected systems, and data-driven decisions are among the technological advancements enabled by Industry 4.0. Industry 5.0, the human-centered industrial revolution, expands upon these themes [8]. Unlike the fully automated processes of Industry 4.0, the collaborative effort of AI-driven automation and human knowledge is at the heart of Industry 5.0 [9]. This means that technology will shift from being a facilitator to becoming a partner in addressing issues of efficiency, economics, human experience, and environmental responsibility [10].

AI AS A TRANSFORMATIVE CATALYST 5.0

Artificial intelligence is crucial for Industry 5.0, enabling smart decision-making, process efficiency, and resource efficiency [11]. By studying and adapting to complex industrial ecosystems, artificial intelligence-powered analytics, machine learning algorithms, and deep neural networks might help make these systems more sustainable. Artificial Intelligence (AI) has the potential to enhance financial viability, reduce environmental impact, and improve worker well-being when utilized effectively [12].

METHODOLOGY

This study examines the perception of AI-based sustainability solutions in Manufacturing 4.0 using a longitudinal approach. Data are collected, processed, and interpreted in multiple modalities over five years. The following parts outline the research approach:

DATA COLLECTION

Conservation System of measurement: The investigated industrial plant will provide data on energy consumption, emissions, and waste reduction. Regular data measurements will track sustainability measures.

- Financial Performance: Analyze corporate financial data for revenue, cost savings, and ROI. Monitor these data across the five-year study period.
- To assess employee happiness, surveys and interviews will be used to measure work-life balance, job satisfaction, and the adoption of AI-driven changes in the workplace.
- A regulator group is established inside the same manufacturing facility. We do not apply AI-driven sustainability indicators to this group, allowing for comparative studies.
- AI Implementation: The experimental group eventually experiences AI-driven sustainability measures according to a specified timeline. Possible actions include automating tedious tasks, reducing waste, and improving energy efficiency *via* the use of artificial intelligence.
- Employee surveys utilize random sampling to provide a representative sample of workers.

TESTING-BASED DESIGN

- The same industrial facility serves as the control group. To enable comparability, AI-driven sustainability criteria will not be applied to this group.
- AI Implementation: The experimental group progressively witnesses the implementation of AI-driven sustainability initiatives, following a predefined timeframe. Waste minimization, AI-powered energy productivity, and repetitive task automation are examples.
- To provide a representative workforce sample, operative surveys utilize random selection techniques.

ANALYSING DATA

- Environmental impact, economic performance, and staff satisfaction will be quantified using descriptive statistics, providing a clear overview of the data. Metrics such as percentages, means, and standard deviations will be included to illustrate trends and variability.
- A comparison of AI-driven sustainability activities is conducted between experimental and control groups to assess their impact. This research

CHAPTER 13

Long and Short Implications of ChatGPT and Generative AI on the Labour Market View

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Abstract: In an effort to offer a systematic understanding of the ups and downs caused by generative AI technologies, this research examines the impact of ChatGPT on the dynamics of the job market. The impacts of ChatGPT may be better understood with the use of the model of supply and demand, which builds upon an examination of the current research. The Global Standard for Occupation Classification is analyzed using a text mining method to determine which vocations are most vulnerable to disruption from ChatGPT. Research shows that Chat GPT has the potential to have a complete influence on 33.9% of jobs, a partial impact on 37.6%, and no impact at all on 31.8%. It is important to remember that the results of this research only show the possible consequences, not the actual impacts, of generative AI services such as ChatGPT on the labour market. When these AI services are extensively used, it will be necessary to conduct more studies to monitor the real changes in employment trends and the dynamics of the labour market. This study presents a nuanced view on both the long-term and short-term impacts of ChatGPT and comparable generative artificial intelligence services on the job market, adding to the area by methodically classifying the degree of influence on various occupations.

Keywords: ChatGPT, Generative AI, Long-term and short-term impacts, Labour market, Partial impact.

INTRODUCTION

OpenAI created ChatGPT, named Chat Generative Pre-Trained Transformer. It gained acclaim for its exact and detailed replies to users' questions [1]. ChatGPT

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has rapidly gained over 105 million monthly users who have been active since its introduction. Public interest appears to be just the tip of the iceberg. Reports indicate that Google, Microsoft, Baidu, and others are attempting to create comparable products [2]. Microsoft is an active investor in OpenAI, and Google just launched Bard, an experimental conversational AI service [3]. Popular Generative AI and large language models include ChatGPT, Bard, Jasper, ELSA, DialoGPT, Chinchilla AI, and Replika [4].

There are several opinions on ChatGPT as well as its impact on global economies, each with valuable insights. Artificial intelligence-powered services have a significant influence on labour forces and the labour market [5, 6]. A substantial amount of literature in labour economics covers automation, robotics, technological advancements, and other innovations in the labour market [7]. As ChatGPT, along with other AI-powered services, automates operations formerly done by humans, it may disrupt certain market areas. ChatGPT is anticipated to have a significant impact on the labour sector, potentially leading to job redundancy and job creation [8]. However, the transition period may present challenges for individuals who require additional training or upgrading to remain competitive in the job market.

A new study aims to predict the impact of AI on the global economy [9]. The primary areas of artificial intelligence encompass image recognition, natural language processing, virtual assistants, robotic process automation, and advanced machine learning [10]. The survey suggests that 70% of organizations have implemented at least one AI technology category, while fewer than 50% have fully integrated all five groups [11, 12]. Artificial intelligence may have a worldwide economic effect of $13.1 trillion by 2030. Potential effects of AI adoption include increased productivity and improved efficiency in other areas. However, various issues might delay AI adoption and utilization. Late-adopting organizations may lag in developing skills and recruiting appropriate talent [13]. AI may have varying impacts on organizations, people, and nations, hindering its optimal use. AI may evolve at different speeds for various nations, organizations, and workers [14]. To maximize its beneficial impact on global economic activity, artificial intelligence must address growing inequalities between countries, enterprises, and workers.

The relationship between AI and the labour market is crucial in the global economy. The influence of AI on employment and occupations is multifaceted, including both good and negative effects [15]. AI may automate operations, leading to job losses in some sectors. Conversely, AI may enable labour and create new jobs. AI will certainly create new job opportunities, such as digital assistant technicians, industrial robotic technicians, and AI marketing professionals. The impact of AI on workers depends on the balance between automation and enhancement, referring to the use of AI to automate or augment jobs in various occupations.

According to experts, the tensions between automation and augmentation characterize the effects of technological advancements on the modern workplace. The potential for automation, augmentation, and job redesign offered by AI should be the focus of researchers and policymakers. Overall, the unforeseen effects of AI must be considered. ChatGPT raised concerns about using AI in everyday life. The article examines the potential economic, political, and societal implications of AI technology. Unregulated AI may hurt competitiveness, consumer privacy, consumer choice, automation, inequality, wages, and political discourse. This author argues that AI costs are not intrinsic but rather tied to their usage and development. Preventing these costs requires regulating AI and directing research towards desirable results. Researchers acknowledge that regulating JEBDE may be challenging, but the potential risks warrant these discussions.

The research aims to analyze how AI-related services, such as ChatGPT, affect various vocations in the labor market. Using supply and demand analysis, we will examine the labor market impact of ChatGPT. This study will focus on both the immediate and long-term effects of this technology on the job market. In conclusion, this is the most effective way to determine which occupations are most vulnerable to AI solutions, such as ChatGPT. A number of AI services, such as ChatGPT, may have an effect on employment. It helps governments and companies manage the effects of fast-changing technology and the workforce.

CHATGPT AND LABOUR MARKET

The impact of generative AI services, such as ChatGPT, on employment and earnings over the medium to long term is examined here using a labour market paradigm. The aggregate labour market is the centre of our investigation. Taxi drivers and cooks are largely unaffected by ChatGPT; however, copywriting and customer service may have a significant impact. Researchers need to categorize jobs according to the level of expertise required to understand how generative AI will impact the job market. Robots and automation threaten low-skilled occupations, while generative AI targets high-skilled occupations.

CHAPTER 14

IoT-Based Indoor Navigation System: Emphasizing Data-Driven Insights for Enhanced User Experience

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Abstract: The purpose of this study was to enhance the user experience in complex interior environments by leveraging data-driven insights, which delve into the internal operations of IoT-enabled indoor navigation systems. A correlation was found between past navigational experience and enjoyment, as determined by user profile analysis. Individuals with much prior expertise reported a satisfaction rate that was 26% higher. Results from the sensors indicated that people are 13% happier in warmer places (in scenarios with an average temperature of 24.0 °C), demonstrating that environmental factors have a significant impact on user satisfaction. Analysis of navigation data revealed that customers preferred customized routes, underscoring the need for adaptable guidance systems. After reviewing user comments, we found that addressing problems increased satisfaction by 19%. Several elements work together to provide a superior experience, including user profiles, environmental simplicity, responsive feedback systems, intricate internal navigation, and personalized routes.

Keywords: Feedback systems, Indoor navigation systems, IoT, User profiles, Warmer places.

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INTRODUCTION

The diverse needs and preferences in indoor navigation have made it increasingly important in urban and institutional settings [1]. The development of Internet-connected gadgets has led to new customer service requirements in complex indoor venues, such as museums, retail malls, and fitness facilities [2]. This study leverages data-driven insights to enhance household navigation through the Internet of Things (IoT) [3]. Complex construction design and weak GPS signals make household traveling difficult [4]. Standard household navigation orders, which often accompany static signs and paper maps, typically fail to provide a good consumer experience [5, 6]. However, IoT-enabled household travel utilizes data reasoning, sensor systems, and mobile designs for tailored, real-time guidance [7]. Smartphone use and the Internet of Things have raised consumer expectations, making improvements to indoor navigation systems necessary [8]. This study investigates the navigation system's action in household travel and suggests ways to develop user knowledge in challenging interiors.

- This research explores household navigation using Internet of Things (IoT) technologies, with a dedicated effort to collecting and interpreting data from sensors inside buildings.
- To evaluate the impact of mathematical variables on the performance of household traveling systems, including gender, age, and level of nautical expertise.
- To determine the effect of tangible factors on household traveling accuracy, in the way of humidity, noise, and hotness.
- Gather consumer feedback and delight ratings to judge the overall depiction of indoor nautical methods that are assisted by one IoT.

The interplay between data and technology is driven by designing and reconstructing household navigation systems. Developers can influence these factors to create consumer-centric, efficient, and custom-built navigation solutions. This method enhances the consumer experience by leveraging IoT-powered household navigation plans [9]. These finishes help companies design household navigation resolutions utilizing their data. This may boost consumer satisfaction and reduce processes [10]. Further applications of the Internet of Things (IoT) to enhance consumer experiences in complex household environments are explored. The project focuses on insights for interior navigation derived from data made available by the Internet of Things. The specific applications may vary, but the general concepts and methods covered here are transferable to many other types of interior spaces. The study's conclusions and recommendations are based on scientific evidence, providing a rock-solid foundation for enhancing indoor navigation systems.

METHODOLOGY

Collecting Information

- Deploying Sensors: The household study background underwent an organized arrangement of an IoT sensor network. Wi-Fi access points, Bluetooth beacons, humidity, and temperature sensors were all involved in this network. In real-time, all of the sensors sent their readings to a principal database
- User Profiling: Before the travel test, a survey was completed as an activity to collect consumer sketches. Respondents' age, gender, and indoor guiding along the route, often over water, records were consistent with the mathematical characteristics desired in the poll.
- Navigation Data: The nautical test compiled a large amount of consumer travel data. This accumulation included opportunity postage, consumer IDs, offset and ending points, and routes. The guiding app along the route, often over water, for travel schemes provides calm navigation in real-time.
- Users had to provide vindication ratings and comments after determining the within-traveling test. The response form included 5-point delight ratings, as well as both fixed and open-ended questions. Feedback was used to assess customer satisfaction and gain qualitative insights.
- Implemented methods that enhanced understanding of service identities, navigation tendencies, and vindication levels, permissive perceptive analysis of within guiding along route, often over water knowledge.

Integrating Data

Learning about inner navigation involves combining data from sensors, user profiles, navigational information, and user input. This combination enables us to provide consumers with personalized ideas while adhering to ethical standards, such as privacy and informed consent. Data handling was discreet and anonymous to protect confidentiality. The indoor, controlled environment may not accurately mirror real-world events, and user feedback may be distorted. The study may have missed other relevant factors. The methodology section outlines a methodical approach to data collection and analysis, aiming to refine the framework and deepen understanding of internal navigation. The project integrates data from multiple sources to provide comprehensive insights into network-of-things-enabled indoor navigation.

CHAPTER 15

Integration of Generative AI and Computer Vision in the Retail Market to Reshape the Industry Dynamics

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Abstract: In this chapter, we present a perspective on how computer vision and Artificial Intelligence (AI) are being applied in retail, highlighting their potential to revolutionize the business. Inventory management, conversational support, personalized shopping experiences, and dynamic outreach are just a few of the ways Artificial Intelligence (AI) is changing the retail industry. This chapter delves into these applications to show how AI is improving customer engagement, streamlining operations, and introducing new products and services. Computer vision has the potential to radically alter shopping experiences *via* self-checkout kiosks, improved inventory management, optimized store layouts, and loss prevention powered by artificial intelligence, according to the research. The chapter argues that AI and Computer Vision are essential for staying relevant in the rapidly changing retail industry and that embracing these technologies is a must. Even if it requires a significant investment of money and training for employees, strategically integrating these technologies opens up numerous doors for development and differentiation.

Keywords: AI, Conversational support, Computer vision, Operational efficiency, Retail sector.

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INTRODUCTION

Logic-based procedures are the foundation of classical computer science [1]. Computer scientists have traditionally viewed algorithms as a set of stages that can be converted into machine-readable instructions and us to solve problems [2]. Over the last 50 years, logic-based algorithms have transformed various business elements, including ERP, supply chain management, industrial processes, sales, presentations, customer support, and commerce. Over the last two decades, corporations have been digitizing their operations, and concepts such as Industry 4.0 have become popular business buzzwords. In contrast, AI has been used to improve the capabilities of computer equipment [3]. In the 2000s, AI was revitalized by three primary influences. The first was Moore's Law, which was the rapid rise of processing power [4]. In the 2000s, computer scientists benefited from increased processing power, smaller form factors, and decreasing computing costs. AI is a promising technology that may facilitate communication between devices and machines, solve issues quickly and accurately, and manage massive amounts of data [5]. In November 2022, OpenAI's ChatGPT emerged as a significant catalyst for the growing interest in AI, specifically generative AI, which it brought to the public's attention. This article gives a comprehensive review of artificial intelligence and computer vision. We believe businesses must recognize the potential of AI and emphasize its importance. Our goal is to help retail businesses understand AI and computer vision better so they can make informed decisions when using these technologies [6]. According to the results of this study, in order to stay competitive and creative in today's technologically advanced world, it is essential to use AI and computer vision [7].

METHODOLOGY

The data used for this study came from academic sources, including Google Scholar and IEEE Xplore, as well as peer-reviewed journals and studies. To compile a comprehensive list of potential resources for our research, we searched for computer vision, Industry 4.0, smart shopping, generative AI, computer vision use cases, and AI use cases in retail.

RETAILING

Companies that offer products and services to customers comprise the retail business. Retail sales and shop kinds such as supermarkets, furniture, reductions, freelances, department stores, DIY, electrical, and specialized stores exist globally. The retail industry continues to develop and employs a large number of individuals globally, especially with the rise of e-commerce. In recent years, the competitive character of this fast-paced sector has increased significantly. In 2022, retail shops must rethink age-old procedures and methods that have shaped the industry. The worldwide shifts in supply chain management for well-known companies highlight the significance of retail sales in the economy. Consumers combine traditional purchasing behaviors with contemporary technologies for ease. They may shop online or in-store using tablets or phones. To meet the rising online purchasing demand, merchants must simplify and speed up customer service. This applies to US retailers, online merchants, and market booths. Retailers must provide excellent service and remain competitive to retain customers.

ARTIFICIAL INTELLIGENCE

The phrase “Artificial Intelligence” (AI) goes beyond computers. This research focuses on building computer systems that can perform tasks typically associated with human intelligence. DeepMind CEO and co-founder Demis Hassabis describes artificial intelligence as the capacity for computers to think and learn. AI-enabled robots can recognize spoken speech, analyze complex data patterns, make informed decisions, and learn from experience. Robots mimic human cognitive abilities, including analysis, understanding, and learning to adapt to new surroundings. Deep learning utilizes complex neural networks to simulate the brain's intricate synaptic architecture. Neural networks like these can understand complicated data patterns, making them ideal for image recognition. AI may help manufacturing, construction, finance, energy, healthcare, and retail. Artificial intelligence allows computers to analyze vast amounts of information, perform repetitive tasks, provide personalized recommendations, and replicate human interactions *via* chatbots and virtual assistants. Despite AI's history, its increasing popularity has led to confusion over its definition and capabilities. Understanding how AI affects contemporary business requires a detailed analysis of its different varieties.

LIFECYCLE OF AI

Identifying the life cycle of AI helps you understand its dangers. Understanding the limits and possible consequences of AI usage is vital for addressing ethical, fair, transparent, and privacy-related issues. For further guidance, refer to the AI Assurance Framework. The data for the AI solution undergoes preprocessing and cleaning to enhance data quality and modeling suitability. Compliance with relevant laws, statutes, and ethical standards remains a core requirement. Meeting product demands often involves applying AI approaches beyond machine learning, such as reasoning, inference, computer vision, knowledge

CHAPTER 16

A Novel Machine Learning-based Web Application for Disease Detection

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Abstract: Disease prediction holds huge value in informed strength planning, providing insights into the prevalence and management of diseases for the implementation of effective interventions and the growth of persuasive health strategies. This work endeavours to develop an inclusive web-based application that leverages advanced machine intelligence algorithms for predicting and reasoning in the fields of breast cancer, heart disease, Parkinson's disease, and diabetes. By integrating advanced predictive models, the application aims to provide consumers with personalized risk assessments for these prevalent healing conditions, supporting early detection and comprehensive care management. Leveraging diverse datasets and contemporary algorithms, the system will provide accurate predictions by enabling more proactive and effective healthcare planning. This multifaceted approach consolidates different energy predictions into a unified framework, streamlining accessibility for consumers and promoting a holistic understanding of their overall health risks. The envisioned netting application holds the potential to transform energy consumption, offering seamless connectivity and empowering individuals to make informed decisions about their well-being.

Keywords: Disease detection, Data analysis, Healthcare, Web application.

INTRODUCTION

Health monitoring should be dynamic, highly personalized, and guided by evidence-based reasoning [1]. Different apps or platforms focus on identifying specific diseases; as a result, overall well-being assessment is usually incomplete.

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This study introduces a web-based interface that integrates machine learning algorithms to forecast myocardial infarction, diabetes, Parkinson's disease, and cardiac cancer [2]. It unifies various well-being predictions into a single, convenient platform, unlike previous systems [3]. User approachability and health risk information are upgraded by consolidation [4]. The state-of-the-art methods and diverse datasets make the proposed platform a significant improvement over the existing approach [5]. This solution encourages users to engage in comprehensive care through early identification and administration by providing correct and tailored risk assessments for many healthcare conditions. This chapter demonstrates that the proposed approach is superior and better positioned to transform health monitoring and enhance healthcare protection. This project focuses on addressing diagnostic challenges and promoting comprehensive health and wellness management. Firstly, the integrated online application addresses a key limitation in healthcare systems—relying on isolated platforms to handle specific health issues [7]. Bringing disease predictions into a single, instinctive interface improves accessibility and consumer engagement by fostering a complete understanding of health risks [8]. Accurate and tailored risk evaluations are possible with modern artificial intelligence algorithms and large datasets. Early identification and intervention are made possible by this predictive healthcare breakthrough [9]. Prevention aligns with modern healthcare paradigms that emphasize proactive over reactive treatments, potentially reducing strain on the healthcare system [10].

LITERATURE SURVEY

Medical diagnostics advanced when Cao, J., *et al*. used Support Vector Machine (SVM) to categorize illnesses based on symptoms. The capacity of SVM to handle complicated datasets and discover patterns offers promise for illness prediction. Parallel computing and algorithmic advancements improve SVM's efficiency for clinical illness prediction.

The hyperplane classification approach was used by Hamidi H. and Daraee A. in their research titled "Analysis of pre-processing & post-processing techniques and using data mining to identify heart diseases." The method achieved limited success in object categorization, and this shortcoming hinders its accuracy, reducing its effectiveness in accurate data classification.

Pisner D.A. and Schnyer D.M [3]. in their study "Support vector machine, in Machine learning" proposed that the hyperplane method demonstrates excellence in classification of sample data into two different groups, but falls short in addressing the healthcare industry's need for multi-class classification. In the current medical context, where the identification of symptoms aligning with various diseases is essential, this limitation becomes evident.

Chen J. and others in their work "Pre-evacuation time estimation located emergency removal imitation in urban dwellings societies", highlight the hyperplane order's skillfulness in segregating sample data into two distinctive classes. However, it emphasizes the limitations in focusing on the multi-categorization needs of medical manufacturing. In the framework of this study, the vital task of mixing manifestations with differing ailments exposes the method's defect. The study stresses the necessity for more complex approaches to fit multiple affliction classes' established symptoms for correct affliction identification. Keniya R., and others in their study achieved the K-Nearest Neighbors (KNN) invention, which determines the data point's class based on the influence of the K nearest data points. However, this form faces the challenge that noisy or missing data poses. Keniya and others. considered variables like exclusive informal networks, syndromes, and gender to call afflictions. Despite this consideration, mixing these limits has resulted in decreased veracity inside machine learning models, obstructing the accomplishment of higher predictive veracity.

This study by Pingale *et al*. introduced the Naive Bayes algorithm for predicting specific diseases, including diabetes, Jaundice, Malaria, Dengue, and Tuberculosis. However, their approach focused solely on a restricted set of diseases. One significant limitation was the absence of experimentation with a sizable dataset for forecasting a broader spectrum of diseases. Consequently, the study's predictive scope remained limited due to the consideration of only a few diseases and the lack of exploration on a larger, more diverse dataset.

METHODOLOGY

The initial phase of disease prediction through machine learning commences with gathering relevant data. Subsequently, the collected data undergoes analysis using various modules, providing a pathway for further examination through machine learning techniques. These modules include:

Heart Disease Detection

By analyzing several health measurements and medical data, the Heart Disease Detection Module employs logistic regression, a fundamental machine learning approach, to estimate risk. The logistic regression model for binary classification is trained using blood pressure, cholesterol, age, gender, and other relevant

CHAPTER 17

A Study on Analyzing the Impact of the Internet on Managing Organizations- Special Reference to the Education Sector

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Abstract: The Internet ushered in the information revolution, facilitating the exchange of information among people worldwide. It is a remarkable innovation in human history that has become accessible to many people worldwide at a very low cost. It has become a major tool for entertainment, conversations, and knowledge sharing. Educational institutions have embraced the Internet to promote and share knowledge. Teachers have created online tutorials, tests, and reading materials to help students improve their knowledge and skills. Textbook writers have begun incorporating web exercises, and web seminars have gained prominence. Given these developments, the role of the Internet in education has become significant. All powerful tools are subject to some misuse. Much like the use of educational television and the internet by students has also been questioned. A spate of articles has appeared in the media discussing the uses and misuses of the internet. .

Keywords: Education, Internet, Management, Organizations, Productivity.

INTRODUCTION

The Internet has registered a speedier growth pattern. By 2005, the number of users had reached the one billion mark, and the second billion was reached in 2010 [1]. The third billion mark is expected to be reached by 2014 or earlier.

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Table **1** illustrates the global growth of internet users [2]. Internet penetration has increased from 6.8% in 2000 to 28.4% by 2010 [3]. Internet penetration refers to the percentage of the population that comprises Internet users [4 - 6].

Table 1. Growth of internet use in the world.

Year	Population	Internet users	Penetration (%)
2022	6,930,725,043	1,996,514,816	28.4%
2021	6,876,479,521	1,786,403,814	25.8%
2020	6,793,732,879	1,775,067,520	23.3%
2019	6,691,607,320	1,473,226,988	20.6%
2018	6,660,220,247	1,262,916,818	17.6%
2017	6,619,635,850	1,130,101,289	15.8%
2016	6,539,842,408	1,110,101,289	14.2%

Asia tops

Table **2** presents the internet usage status in various regions for 2022. Out of the world's Internet users, Asia has the most, accounting for 42 percent of the global total. The next region is Europe, with 24.2 percent. North America followed with 13.5 percent, and Latin America with 10.4 percent of users [7].

Table 2. Internet usage in different regions – 2022.

World Regions	Internet Users June 30, 2022	Internet Users %
Africa	110,931,700	5.6%
Asia	1,825,094,396	42.0%
Europe	675,069,448	24.2%
Middle East	68,240,946	3.2%
North America	566,224,500	13.5%
Latin America/Caribbean	204,689,836	10.4%
Oceania / Australia	21,263,990	1.1%
World Total	1,966,514,816	100.0%

Source: Top 15 Countries in Internet Usage, 2010 – Infoplease, www.infoplease.com › ... › Internet Statistics and Resources.

Table 3. Top 20 internet users in the world.

S.No	Country	Users of internet (mn)	Population (mn)	Penetration (%)
1	China	420.0	1330.1	31.6

(Table 3) cont.....

S.No	Country	Users of internet (mn)	Population (mn)	Penetration (%)
2	United States	234.4	307.2	76.3
3	Japan	99.1	126.8	78.2
4	India	81.0	1173.1	0.7
5	Brazil	72.0	198.7	36.2
6	Germany	65.1	82.3	79.1
7	Russia	59.7	139.4	42.8
8	United Kingdom	51.4	62.3	82.5
9	France	44.6	64.8	67.9
10	Nigeria	44.0	152.2	28.9
11	South Korea	39.4	48.6	81.1
12	Turkey	35.0	77.8	44.9
13	Iran	33.2	76.9	43.2
14	Italy	30.0	58.1	51.6
15	Indonesia	30.0	243.0	12.3
16	Philippines	29.7	99.9	29.8
17	Spain	29.1	45.6	63.8
18	Canada	27.6	111.2	24.8
19	Mexico	25.1	33.5	74.9
20	Vietnam	24.3	89.6	27.1

China tops, and India is in fourth place.

Table **3** presents the number of internet users in various countries for 2022, listed in descending order. China is the top nation in terms of population and Internet users [8]. The next one is the United States in terms of internet users [9]. India is the fourth-largest country, after Japan. Internet penetration shows different results. The United Kingdom has the highest internet penetration at 82.5 percent [10].

INTERNET SPEED – KOREA LEADS

According to Akamai's eleventh quarterly State of the Internet report, South Korea leads all other countries with its fastest internet connection speeds of 16,63 Megabits per second (Mbps). The average connection speed for Internet users worldwide is approximately 1.8 Mbit/s. Table **4**.

CHAPTER 18

A Hybrid Model for Multilevel Thresholding Segmentation for Detecting Leaf Disease in Groundnut Plants

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Abstract: A hybrid segmentation technique is used in this chapter. It is one of the approaches for detecting agricultural diseases in groundnut plant leaves using the multilevel thresholding segmentation method. Various comparative analyses were done using soft computing techniques. In this work, the Krill Herd algorithm and Dragonfly algorithm are employed to achieve global and local optimization, thereby enhancing the accuracy of disease detection in groundnut plant leaves. The proposed hybrid method is named the Enhanced Krill Herd- Dragonfly algorithm (EKHD algorithm). The robustness of the EKHD algorithm was verified in the experiment results. The various pre-processing methods and color image segmentation methods were used for disease identification, and the proposed method gave more accuracy than the existing methods. This segmentation method can be used to identify the affected portion of the plant leaves. The proposed method demonstrates the accuracy of the experimental results.

Keywords: Krill-herd algorithm, Multilevel thresholding, Segmentation.

INTRODUCTION

Agriculture plays a major role in the Indian economy. India is a diverse country gifted with vast physiographical & climatic conditions [1]. This climatic condition is well-suited for crops such as nuts, fruits, and vegetables at the same time [2]. Every year, a large number of crops are lost due to poor climatic conditions or disease invasion [3]. These circumstances aggravate the issues that cannot be ignored or eradicated permanently [4]. Among these factors, disease detection in a

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plant leaf is the most serious hazard to harvests [5]. Due to their external exposure, plants are easily susceptible to diseases [6]. Various applications have been developed for identifying diseases in agricultural plants. Detection of diseases in the growing plants at the initial stage is the most critical for preventing significant crop losses [7, 8]. Due to workforce shortages and rising fertilizer costs, production costs are increasing while yields are decreasing [9]. These are the primary repercussions that farmers confront in the current conditions. To improve the quality and quantity of products, it is essential to explore new technologies [10]. Various techniques are employed to identify different types of diseases in a wide range of plants.

METHODS AND MATERIALS

Using an integrative image processing approach, the developed technology recognizes and classifies Groundnut leaf disorders. A filter is used to pre-process the collected photos, and a Multiple thresholding technique is used to segment the pre-processed color leaf images.

Groundnut Plant and Its Diseases

Groundnut leaf diseases are primarily classified into three categories: bacterial, fungal, and viral. Bacterial Blight, Anthracnose, Alternaria, and other diseases, along with pests, cause damage to groundnut plants. Image processing techniques are utilized to recognize certain disorders. Image processing techniques are employed to detect specific disorders. In this chapter, these techniques are used to identify and cluster groundnut diseases. The pre-processed images of plant leaves were acquired and subjected to further analysis using this approach (Fig. **1**).

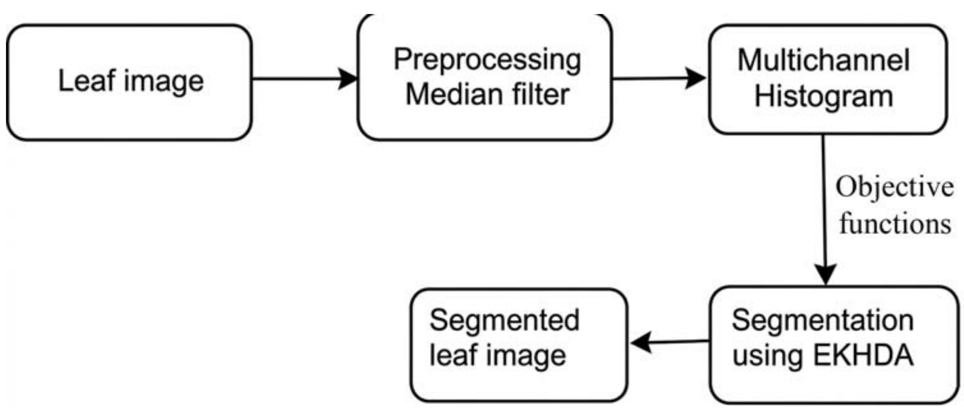

Fig. (1). Flow chart of the proposed methodology.

Image Acquisition

Digital image processing is used to capture the input images of diseased groundnut leaves. To facilitate evaluation across vast fields, an automatic leaf detection method is used to identify and locate affected leaves. The captured images are then transmitted to the processing system for further analysis.

Preprocessing

Data acquisition and preparation are the most important steps in image processing. When it comes to detecting groundnut leaf diseases, the quality of the images is crucial. Pre-processing is essential in electronic data mining, particularly in the filtering and contrast enhancement stages for diseased leaves. Pre-processing is more likely to be associated with leaf segmentation. This step ensures that the high-quality images of groundnut leaves are captured with maximum accuracy. Initially, images with a pixel range of 0 to 255 are used; therefore, the gray level values must be normalized to a range of 0 to 1 for further analysis. Following normalization, the features are extracted and utilized in subsequent filtering and segmentation processes. In this chapter, the median filter is applied during the pre-processing stage.

The Median Filter

The input images have high impurities and improper pixel brightness. As a result, image denoising is crucial for enhancing image quality by reducing noise. Due to noise, image quality and feature extraction become unreliable. In this chapter, a non-linear filter is utilized to denoise the data.

Median filters use the pixel window to calculate the output. Pixel windows can be any size and shape (often odd numbers). Fig. (**2**) illustrates the selection of a 5x5 square size for the proposed work, as it is more than sufficient to function effectively while being less than optimal for achieving efficiency in a picture. The median filter is the most effective windowing operator. The fundamental assumption of the median filter is to examine the sample value of the input pictures to see whether it is representative of the image.

Multi-Threshold-Based Color Segmentation

Segmentation is a process of dividing an image of an infected plant leaf into multiple segments or fragments, enabling the extraction of specific regions for

CHAPTER 19

Transformer-based U-net Model for Segmentation of Paddy Leaf Disease

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Abstract: Paddy leaf disease is a common problem in rice cultivation. These diseases can significantly impact crop yield and quality. Several types of disease can affect paddy leaves, and each has its own characteristics and management strategies. Segmenting paddy leaf diseases is a crucial process for identifying and separating areas of an image that exhibit signs of disease from healthy areas of paddy leaves. This process plays a crucial role in agriculture for early disease detection and management. It is an open challenge for researchers to identify an efficient segmentation technique to strengthen precise early disease detection. Therefore, this study developed a transformer-based U-net (TransUNet) model for segmenting paddy leaf disease. Three different paddy leaf disease images are utilized to train and evaluate the TransUNet model. The performance analysis reveals that the TransUNet model achieved higher segmentation accuracy, with pixel accuracy and mean pixel accuracy values of 0.9964 and 0.9974, respectively.

Keywords: Agricultural images, Paddy leaf disease, Segmentation, Transformer block, U-Net model.

INTRODUCTION

Effective disease management in paddy cultivation typically involves a combination of cultural practices, such as crop rotation and maintaining proper field hygiene, using disease-resistant rice varieties, and, in some cases, applying chemical treatments (fungicides or bactericides) [1]. Early detection and regular monitoring of paddy fields for disease symptoms are crucial for timely intervention and preventing yield loss [2]. Several types of diseases can affect paddy leaves, and each has its own characteristics [3, 4]. Rice blast, sheath

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blight, rice tungro disease, bacterial streak, false smut, bacterial leaf blight, brown spot, and leaf smut are common paddy leaf diseases. Bacterial leaf blight is caused by the bacterium [5, 6]. Water-soaked lesions that appear as small, dark green spots on the leaves. Brown spots are caused by fungus. Symptoms include small, dark brown to black lesions with a yellow halo on the leaves. Leaf smut, caused by the fungus, produces black, powdery spore masses on the leaves [7]. Early detection and regular monitoring of paddy fields for disease symptoms are essential for timely intervention and prevention of yield loss [8, 9]. Crop monitoring and capturing leaf images can be done using cameras or mobile devices [10]. Different Convolutional Neural Network (CNN) models, such as U-Net, Mask R-CNN, and SegNet, are commonly used for segmentation models in crop leaf disease detection problems. Post-processing steps are necessary to refine the segmentation results and improve segmentation accuracy [11]. Moreover, Morphological operations such as erosion and dilation can be integrated with the segmentation model to improve the accuracy of the segmentation mask. The crop leaf disease region segmentation helps to calculate the percentage of affected areas and can count the number of lesions to assess the severity of the infection. Implementing the system in real-time or periodic monitoring of paddy fields to detect and manage disease outbreaks [12]. The success of the segmentation model largely depends on the quality and quantity of the training data, the choice of architecture, hyperparameter tuning, and the quality of preprocessing and post-processing steps. Regular updates and retention of the model might be necessary as new images become available. It is an open challenge for researchers to identify an efficient segmentation technique that enhances precise early disease detection. This study focuses on developing a paddy leaf disease detection method using a segmentation model to enhance disease detection accuracy.

The rest of the section is organized as follows: Part II describes the related study on plant leaf disease detection and recognition techniques based on research. Part III describes the methodology adopted in this study in detail, and Part IV presents the performance analysis of the Transnet model. Part V concluded the research findings and future enhancements.

PADDY LEAVE DISEASE DETECTION APPROACH USING ENHANCED TRANSFORMER-BASED U-NET MODEL

Image Acquisition

Illumination changes and voltage fluctuations in the camera sensor are common sources of image noise in digital color images. Generally, it looks blue in color in the underexposed image. The Gaussian smoothing approach is utilized to reduce the blurred noise in the input leaf image. It computes the Gaussian transformation for each pixel of the input leaf images to identify and smooth the intensity values of the corrupted pixels.

$$g2(s,t) = \frac{1}{2\pi\sigma^2} e^{-\frac{s^2+t^2}{2\sigma^2}} \quad \textbf{(1)}$$

The Gaussian smoothing union g2(s,t) represented in eq (1). The derivation ($\frac{1}{2\pi\sigma^2} e^{-\frac{s^2+t^2}{2\sigma^2}}$) computes the Gaussian distribution for each pixel using the intensity of all neighbouring pixels in a given window size to replace the corrupted pixels. The notation s and t indicate the smoothed pixel position of an image in the coordinate axis, respectively. The notation σ is used to compute the standard deviation. This function creates the convolution matrix for the actual input leaves image and a weighted average is added to each pixel's neighbors. The original pixel values receive the highest Gaussian value, and its neighbouring pixels receive smaller values. Therefore, this approach helps to preserve the edge information of the input image.

TransU-Net model for detecting paddy leaf diseases.

The segmentation model utilizes the functionality of the U-Net model and combines the spatial attention module within the transformer block to construct the TransU-Net segmentation model. It is specially designed for biomedical image segmentation. This study focuses on segmenting three paddy leaf diseases, such as bacterial leaf blight, brown spot, and leaf smut. These three diseased leaves are utilized to evaluate the functionality of the segmentation model. The original U-Net model consists of two parts: an encoder and a decoder block. Fig. (**1**) illustrates the overall functionalities of the TransU-net model.

This TransU-Net model has three main functionalities the DS level, the transformer block and the Up-Sampling level.

Downsampling

The upsampling level is the first half of the TransU-net model. It is also known as an encoder block in the U-net model. A convolutional function is followed by two max and average pooling operations to encode the image into feature representations at multiple levels. The TransU-net model uses five -sampling (DS) levels, including D1, D2, D3, D4, and D5.

CHAPTER 20

A Study on Factors Influencing Consumer Buying Behaviour on Health Drinks with Special Reference to Palakkad District

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Abstract: "A Study on Factors Changing Customer Decisions on Health Drinks in Special Reference to the Palakkad District" examines the intricate network of variables influencing health drink customers' decisions, particularly in the socially diverse and affluent district. Understanding client options in Palakkad is crucial, given the rapid growth of the global wellness and healthcareindustry. Due to its socio-cultural dynamics, this area is a good example of examining local causes and health awareness trends. The chapter contributes to the understanding of consumer behaviour, particularly in the fast-growing health drink sector, thereby enhancing both academic and practical expertise. A systematic approach to data collection, analysis, and interpretation sheds light on aspects of consumer behavior in the Palakkad District. This chapter helps health drink makers and marketers understand customer preferences and create customized marketing tactics.

Keywords: Consumer buying behaviour, Consumer preference, Health drinks.

INTRODUCTION

The use of nutritious drinks has seen an even more dramatic shift in consumer behavior than the general trend of shifting consumption patterns [1]. In this regard, the chapter "A Study on Factors Influencing Consumer Decisions on Health Drinks with Particular Application to the Palakkad District" is particularly relevant [2]. With a focus on the culturally rich and economically diverse Palakkad District, this chapter aims to examine the web of factors influencing health drink purchase choices [3].

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Given the expected growth in the global health and wellness industry, it is vital to understand the factors that influence consumer choices in Palakkad [4]. This location, renowned for its distinctive sociocultural dynamics, is a fascinating example of how regional influences intersect with national health awareness efforts [5, 6].

Health drink consumption has undergone substantial changes [7]. As such, "A Study on Factors Influencing Consumer Choices on Healthy Beverages with Particular Regard to Palakkad District" matters. In Palakkad, a culturally diverse and prosperous region, this chapter will investigate the complex factors that influence the choice of health drinks. Understanding the choices of Palakkad customers is crucial as the global health and wellness industry continues to grow [8, 9]. Its distinct socio-cultural dynamics make this region a remarkable example of regional causes and health consciousness trends. This survey will help health drink marketers and firms understand client preferences for health products [10]. Regional consumer behavior patterns and health drink manufacturing and marketing are discussed in the study, with a focus on Palakkad District [11].

Specifically for the rapidly expanding health drink industry, the chapter "A Study on Factors Influencing Customer Decisions on Healthy Drinks with Particular Regard to Palakkad District" contributes to the body of knowledge on consumer behaviour [12].

LITERATURE REVIEW

Consumer behavior, health advertising, and local consumer analysis inform "A Study on Factors Influencing Customer Decisions on Healthy Drinks with Special Attention to Palakkad District." The literature review outlines past results and indicates areas where this chapter may bring additional insight.

The knowledge depends on consumer behaviour research in health-related goods marketplaces. Kumar and Sharma (2019) examined consumer buying patterns and emphasized the increasing importance of health information in purchasing decisions. Their results indicate that buyers are prioritizing health-related items and making more informed purchasing decisions. Numerous studies have shown that demographics affect consumer behaviour. Johnson *et al*. examined how age, gender, and wealth affect health product choices in 2020. They found substantial differences in the preferences and purchasing behaviors of these groups. This is crucial to understanding Palakkad's customers. Psychographic factors, including lifestyle and beliefs, affect healthy drink choices, according to Chen and Lee (2021). They believe lifestyle and health knowledge determine preferences. Patel's (2022) regional research demonstrates how economic and cultural factors in India influence consumer preferences. This research is crucial for understanding the unique conditions of Palakkad. Packaging, price, and branding are recognized as factors thatinfluence customer purchasing decisions. Singh and Gupta (2023) examined how these factors and marketing affect customer perceptions and purchases of health drinks.

Digital marketing has led to studies on how the internet and marketing affect customer perceptions and choices. For example, Sharma and Ali (2021) conducted research that highlights how digital platforms are increasingly influencing consumer choices, particularly among younger audiences. Comparative research, such as that by Lee *et al*. (2020), highlights the variation in consumer behavior across different geographical and cultural contexts. These studies help uncover differences in consumer behaviour in Palakkad District compared to other places.

This literature provides a comprehensive understanding of health drink customers' purchase choices. Local studies are scarce, particularly in the Palakkad District, where economic, cultural, and social issues may influence consumer behavior. This research aims to fill this information gap by providing Palakkad-specific insights and enhancing the understanding of healthy drink consumer behavior.

OBJECTIVES

1. To identify the key factors influencing consumer purchasing decisions.
2. To analyse the preferences and perceptions towards different health drink brands.
3. To examine the impact of demographic variables on buying behaviour.

Significance of the Study

- The different demographics of the Palakkad district provide a unique framework for researching consumer behaviour.
- This research will help health drink makers and marketers understand customer preferences and create tailored marketing tactics.

RESEARCH QUESTIONS

1. What are the primary factors influencing consumers' decisions when purchasing health drinks?
2. How do consumers perceive various health drink brands available in the Palakkad district?
3. What role do demographic variables (age, gender, income) play in influencing consumer buying behaviour of health drinks?

CHAPTER 21

Machine Learning Model: Operating Machinery Status for Fault Prediction

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Abstract: Recent firms prioritize smart machinery monitoring. Smart machines will generate more data, and internet bandwidth will impact both data transfer speed and the reliability of equipment monitoring platforms. This study proposes creating an upload event using machine production data to reduce periodic information submitted to the monitoring platform. The proposed solutions minimize bandwidth and electricity. Historical data will not decrease cloud server database storage since the recommended approaches recreate monitoring information. The suggested method utilizes machine learning technology to predict equipment faults, thereby reducing downtime. The IoT-based smart equipment monitoring solution reduces transmitted information by 54.58% and achieves 99% prediction accuracy in experiments.

Keywords: Internet of Things, Machinery Monitoring, Minimize Bandwidth, Machine-Learning Technology, Platform Dependability.

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INTRODUCTION

Smart machine creation and utilization enhance manufacturing and management efficiency [1]. The term “Industrial Internet of Things” has come to describe the use of the Internet of Things in intelligent machinery [2, 3]. Worldwide, the equipment industry employs smart machines and computerized assembly lines. This technology began with a real-time production data platform [4]. Ball-bearing malfunction inspections, remote turbine condition tracking, smart maintenance vibrating monitoring, vibration time histories, and industrial data-driven monitoring might utilize this data. The monitoring platform sends all of the plant's data, such as fault signals, power, present, and process status, to the manager *via* the Internet, allowing him to make decisions using data visualizations and smart analysis to reduce failures of machines, such as monitoring the health on marine vessels, developing a framework for identifying faults in predictive maintenance, and peak-load [5, 6]. Manufacturing parameters are frequently sent to the cloud server monitoring stage over the Internet because the machine equipment controllers process hundreds of production parameters during manufacturing. In addition to wasting Internet bandwidth, the long production period for equipment manufacturing components and electronic parts increases the risk of stretching and wear from rotation or movement, making real-time monitoring difficult [7, 8]. After storing production parameters data and abnormal condition recognition device data in the cloud-based monitoring stage, the entire scheme can perform preventative maintenance analysis on the data for every manufacturing component, enabling early substitution and repair of manufacturing devices or electrical parts, component dressing, and preventing mechanical equipment downtime and other property loss. Prediction accuracy is influenced by the major operational factors involved in detecting and identifying in a real-world industrial system [9].

This paper proposes establishing a return occurrence induction based on the changing features of the mechanical equipment's production parameter data and customizing the tolerance value based on each piece's parameter values to minimize the upload of manufacturing parameter information to a cloud-based actual monitoring stage. Continuous monitoring of the transmission to the cloud-based servers' system would be reduced to a lower frequency, which would considerably decrease the amount of production parameters information as well as sensor device data for abnormal conditions, thereby decreasing internet traffic and database stress. This paper also suggests analyzing and modeling past abnormal information data from mechanical equipment to identify components or electronic parts that need replacement or repair, thereby reducing property losses resulting from mechanical equipment downtime. Computational approaches help machine-learning algorithms acquire advanced knowledge, but classification design and planning remain crucial [10]. To reduce motorized equipment downtime and early manufacturing component or electronics component failures, this study recommends employing irregular condition detection element information for equipment failure, evaluation, and modelling. First, second, and third-second individual values, normal values of the initial and subsequent seconds, and average values of each of the three seconds are classification characteristics [11]. This chapter created the first smart equipment tracking system for bottle-bursting machines using machine-learning methods. The suggested system architecture and methodologies are presented in Section 3. They explain the experimental conditions and findings in Section 3. Section 4 concludes this study.

METHODOLOGY

This work utilizes reduced data broadcast, high-accuracy mechanism status analysis, and maintenance forecasting to monitor machines and reduce standstill time.

Minimized Data Transfer

Two ways to limit data uploads to the Smart Machinery Management System. Comparing recent and old data is the first technique. As indicated in Fig. (**1**), the newest data is uploaded if the disparity exceeds the tolerance threshold, and vice versa. The second technique may determine whether to submit data to decrease uploads. Fig. (**2**) compares the current C, D, E, and G values to the preceding data. While the D and E numbers remain identical as before, the C and G standards are linearly decreasing and increasing, respectively. They won't be posted since their alterations match the record. Non-related values will be submitted in JSON format. As per the guidelines, the cloud server databases will add a parameter value if it is not received. The cloud server will compute the slope using the two most recent database entries when the upload request is received. The cloud server databases receive missing values using linear interpolation.

Machine Status Analysis with High Accuracy

Fig. (**3**) shows how a high-pass sieve will capture high-frequency acceleration data from machine vibration readings. Due to the three-second cycle time of the machine studied in this paper, the samples were computed by averaging the acceleration values collected after the first two seconds, the subsequent two seconds, and all three seconds.

CHAPTER 22

Development of Forecasting Models to Predict the Power Consumption of Charging Stations: IoT

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Abstract: Owners of electric vehicles face the challenge of having a limited number of charging station options. A feasible solution to this issue might be the installation of individual charging stations near residential areas. Access to a reliable forecasting model that can accurately predict the power consumption of these stations would enable station owners to plan their energy generation better. The objective of this study was to propose a charging station technology that enables electric vehicles to connect through the Internet of Things (IoT). The study introduces an ARIMA-based model that, by optimizing parameters, can fit its learners into the station's subgroups to improve overall sales prediction. With an average MAPE of 13.89%, an RMSE of 6.68%, and an R^2 value of 1.80%, the proposed model successfully forecasted electricity consumption for seven charging stations.

Keywords: Charging station, Electric vehicles, IoT, MAPE, RMSE.

INTRODUCTION

The automotive industry is undergoing rapid transformation due to the growing popularity of electric cars. Electric charging stations must be built in large numbers to accommodate this demand [1]. The average cost to establish a charging station for electric vehicles is 24 00,000 INR. Getting land cover and keeping the power on consistently account for most of the expenses [2]. Installing electric vehicle charging stations in neighbourhoods might be a practical way to provide more affordable land [3, 4]. Electricity prices may be reduced by

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generating power from renewable sources. Smart charging stations, which are internet-connected, enable users to reserve a charging spot in advance through a web interface or a mobile app [5]. Smart charging stations may be useful here, but automating the charging process and predicting usage on any given day would be a challenge [6]. An Internet of Things-based, networked electrical charging station, comprising a system of online-bookable automatic charging stations, is proposed as a solution to these problems [7, 8]. Using an approach derived from the ARIMA model, they predict daily revenue associated with the charging station. This helps manage the station's energy supply properly [10].

SUGGESTED APPROACH

Charging stations connected to the Internet of Things (IoT) are being set up and can be reserved online. There is a connection between the cloud and the charging stations. Charging stations utilize a relay module and a current sensor. Regular uploads to the cloud are made of the data collected from the sensors.

Every customer's details who reserved a charging station are recorded. An authentication token will be provided to customers, allowing them to access the charging station. The consumer can choose the charging percentage online, and the current sensor controls the charging process accordingly. The power supply of the charging station may be turned on and off using the relay module. The cloud is where it is updated after the charging procedure is finished.

Customers may reserve a charging station by selecting their desired location and consulting the website. The website automatically updates the list of charging stations according to the user's current location. When the consumer arrives at the assigned charging station location, they can use the station by entering an authentication token that was sent to them when their booking was confirmed. Based on the availability, the website updates the list of charging stations in a place hourly, as illustrated in Fig. (**1**).

The booking details are saved in the cloud, and the authentication tokens are sent to the designated charging stations. The next step is to approve consumers using the authentication token. After every successful order, the status of the charging station is updated, which in turn updates the list of readily accessible stations. In an ideal world, customers would have access to charging stations similar to those shown in Fig. (**2**).

An area's seven charging stations provided the data used to build a model for energy consumption forecasts based on machine learning. Several charts are generated from the dataset after it is exposed to Exploratory Data Analysis (EDA) to gain insight into the sales of products at different retailers over time. Following that, feature engineering is used in the dataset to extract relevant sub-features from the initial features. To build a more robust machine learning model, feature engineering is used to increase the dataset's dimensionality. Separate parts of the dataset are used for training and testing purposes. The prediction model is built using time series forecasting after the data is split.

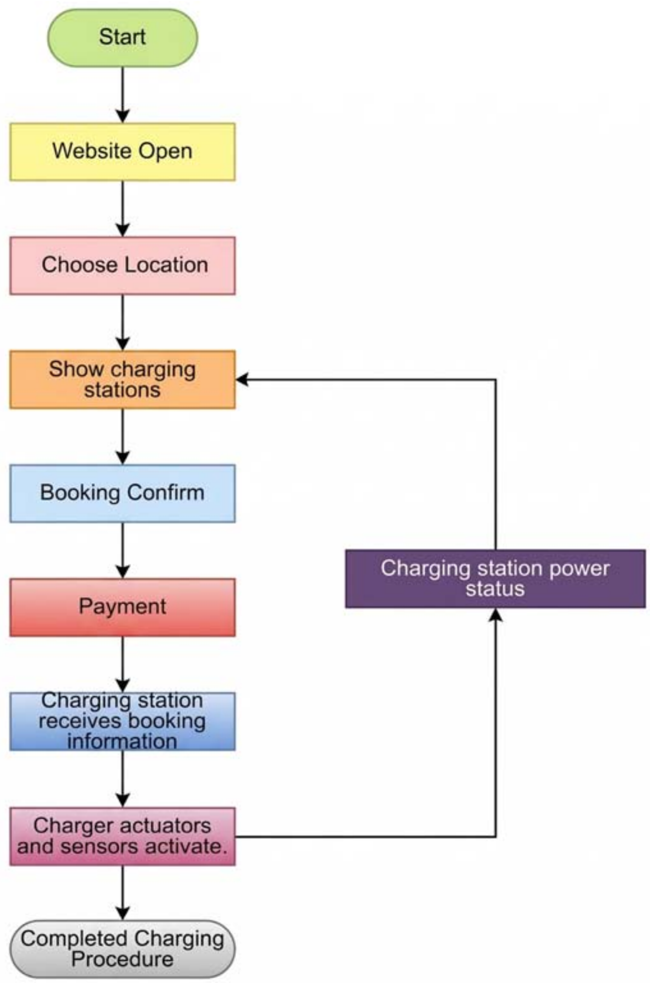

Fig. (1). Website updates the list of charging stations.

THE IMPLEMENTATION

The system comprises six charging stations, which receive data from the cloud, where the website's purchase details are stored. Moreover, the customer's car is physically charged to the specified percentage. The following sections outline the process of implementing the planned system.

CHAPTER 23

IoT-based Detection System to Support Electric Vehicle Charging Stations

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Abstract: There has been a meteoric rise in the demand for electric vehicles. A secure environment that caters to users' needs is necessary to achieve this goal. The IoT network enables the collection of data from Electric Vehicle (EV) charging stations. The use of EVCSMSs, or systems for managing charging stations, allows this to happen. Cyber-attacks on IoT devices are becoming increasingly common, posing a growing threat. Traditional information technology systems heavily rely on Intrusion Detection Systems (IDSs) to aid in identifying malicious traffic. This chapter presents a classifier technique that uses machine learning to identify fraudulent communications in an IoT setting. All of the data used by the suggested system comes from actual Internet of Things (IoT) traffic. Various classification algorithms are tested. Both multiclass and binary traffic models yielded results. Electric car charging stations that utilize an Internet of Things (IoT)-based Intrusion Detection System (IDS) engine would benefit from the proposed methodology, which would reduce the frequency and severity of cyberattacks that could disrupt daily life.

Keywords: Charging stations, Cyber-attacks, Electric vehicle, IoT, Intrusion setection system.

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INTRODUCTION

IoT has entered our everyday life [1]. The cybersecurity of IoT devices has raised concerns among network operators and consumers [2]. Electric vehicle charging facilities are expanding in smart cities [3]. Many countries require the rapid implementation of EVCS [4]. EVCS operators may simplify and regulate their lives with new IoT charging stations. The Internet is essential for the EVCS, as it is an IoT device [5]. Comprehensive client service is the goal. This, unfortunately, allows cyberattacks to target the entire EVCS ecosystem [6]. EVCSs are not the only ones affected. It affects both essential power grid infrastructure and close consumers correspondingly [7]. The EVCS ecosystem consists of the electricity grid, EVCS, and end consumers. All EVCS ecosystem components are vulnerable to various IoT cyberattacks [8]. Rapid infrastructure development is necessary for sustainable growth in the EVCS business. The formation of a stable charging station ecosystem is essential for electric automobiles [9]. Electric vehicle charging stations provide valuable data *via* the IoT network, enabling developers to offer end-user benefits such as remote monitoring and accounting [10]. A noteworthy feature is the ability to remotely schedule EV charging based on lower power costs at night [11]. In IoT cybersecurity, identifying malicious traffic from genuine communication is challenging. Advanced attackers employ sophisticated tactics to conceal their activities. IoT security requires more attention than typical IT network security. The large attack surface and several weak spots result from data sharing and continual communication between nodes to service consumers. Detecting hostile traffic in IoT and IT systems relies on intrusion detection coordination, which is constantly improved for efficiency and accuracy. Using a meaningful dataset is crucial for evaluating IDS systems. In academics, deep learning and machine learning algorithms have led to more efficient and accurate detection techniques for various intrusions employing Intrusion Detection Systems (IDSs). Recently, the costs of energy sector breach data have soared, according to a study. This study provides ML methods for EVCS cyber-attack detection.

The approach comprises gathering and refining data from the charging process, the charging station's network traffic, and the surroundings. ML models are trained and evaluated to identify and classify cyberattacks using this data. This research evaluates ML algorithms and reveals the most effective approaches for detecting attacks on EVCSs.

This article outlines the charging EV ecosystem, from the EVCS to the EVCSMS management system, utilizing communication and transportation protocols. Researchers outline important assaults, attack avenues, and vulnerabilities in each component of the ecosystem. These assaults may target charging stations, users, and the power grid, which is the most damaging sort. Additionally, there is anomaly detection using machine learning and traffic representation using the IoT dataset. The IoT data provides usual traffic in IoT schemes, using the EVCS as an instance. The dataset indicates potential traffic and assault incidents on the EVCS. So, they utilize IoT-23, a native IoT dataset. It is based on genuine IoT devices. Additionally, to improve algorithm agility, unnecessary duplicated characteristics are first removed from the dataset. This improves accuracy and eliminates overfitting and underfitting in these models. By utilizing machine learning to identify EVCS hacks, we aim to enhance the security and reliability of EV charging infrastructure.

This study's contributions include the application of various machine learning methods to detect malicious traffic in EVCSs, utilizing native IoT data. Discuss EVCS attacks, vulnerabilities, and mitigation measures conducted in the literature. Apply machine learning methods from non-Internet of Things (IoT) security issues to IoT security issues. Detect malicious traffic with minimal training data and a smaller dataset.

The chapter continues as follows: The setting of the issue is described in Section 2. Section 3 describes the simulation approach and components utilized to simulate the actual situation. Experimental outcomes in Section 4 show the performance of several ML classifier methods. Limitations and conclusion are discussed in Sections 5 and 6.

EV CHARGING STATION BACKGROUND

As a new system, EVCS has several attack surfaces. State-sponsored actors and competitors attack it because of this. As more EVCS units connect to the Internet, adversaries may exploit vulnerabilities to hack both public and private EVCSs. Weak EVCS network access restrictions can allow exploitation of distant Internet or Local Area Networks (LANs).

The EVCS has detection, networking, and communications layers involved. Attackers focus on communication and networking, the most susceptible parts. This layer communicates with SCADA. This layer also provides Internet connectivity between the EVCS and the final user. This can be done *via* Bluetooth, Wi-Fi, cell phone, DSL, or fiber optics. Other EVCS components, such as sensing and computing, are internal. They are susceptible but need local contact with the EVCS or may be exploited once communication and networking compromise the EVCS.

CHAPTER 24

Diabetes Prediction Using Supervised and Unsupervised Machine Learning

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Abstract: This study uses health indicators and supervised and unsupervised learning to predict diabetes. Principal Component Analysis produced complex data structures; however, unsupervised exploration revealed the strongest connection (0.57) between glucose levels and diabetes. At K≈11, supervised learning achieved 85.6% accuracy using a K-Nearest Neighbors (KNN) classifier. Good discrimination was shown by its low false optimistic rate (0.1%) and high true optimistic rate (0.86). Quadratic Discriminant Analysis (QDA) exhibited a lower TPR of 0.75 than LDA at the same FPR. Diabetes prediction using KNN and LDA yielded promising results, highlighting the importance of both specificity and sensitivity. The choice of model should be based on interpretability, computational efficiency, and ROC analysis. This diabetes prediction study may aid in clinical decision-making and future research.

Keywords: Diabetes, K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Prediction, Quadratic Discriminant Analysis (QDA), Supervised learning, Unsupervised learning.

INTRODUCTION

Diabetes, characterized by high blood glucose levels, affects individuals and healthcare systems worldwide [1]. The global diabetes pandemic underscores the need for effective prevention, diagnosis, and treatment of diabetes [2]. Because undiagnosed or poorly controlled diabetes increases the risk of circulatory disease, renal failure, sightlessness, and neuropathy, this study was prompted [3]. Machine Learning (ML) enables doctors to reveal complex relationships in massive health indicator data and incorporate them into prediction models [4]. In this research, we will utilize blood pressure, glucose, and BMI to predict diabetes using both

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supervised and unsupervised learning [5]. Unsupervised methods, such as Principal Component Analysis, help us understand data structures and identify diabetes risk factors [6]. Supervised learning prediction models, such as KNN, LDA, and QDA, will then be tested for sensitivity, specificity, and accuracy [7 - 11].

METHODS USED

In this study, we investigate diabetes prediction using two distinct approaches: unsupervised learning with PCA and supervised learning methods such as K-NN, LDA, and QDA. The Pima Indians Diabetes dataset is being examined, and it contains data from 500 non-diabetics and 268 diabetics. This dataset contains nine columns and 768 rows of information about various health indicators, including the number of conditions, glucose levels, blood pressure readings, and more. As shown in Fig. 1, our study independently evaluates each approach. First, we use unsupervised PCA to reduce the dataset's dimensionality and find patterns or clusters. This exploratory analysis will reveal the dataset's structure without diabetic labels. We then create labeled data-only predictive models using supervised learning methods, such as KNN, LDA, and QDA. Applying each method individually to the original dataset without dimensionality reduction will determine its performance in classifying diabetics versus non-diabetics. Our study uses the Pima Indians Diabetes dataset to examine how unsupervised and supervised learning methods predict diabetes.

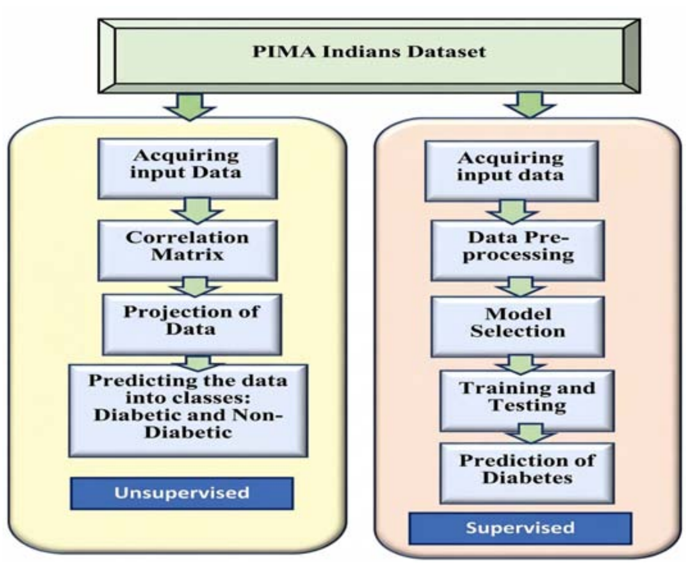

Fig. (1). Block diagram for the detection of diabetes.

Unsupervised Learning

In this work, we use Principal Component Analysis (PCA) to investigate diabetes prediction using unsupervised learning. It is a powerful dimensionality reduction technique widely used in prediction algorithms and machine learning applications through principal components. PCA begins by standardizing the features. This step ensures that all features contribute equally to the analysis, avoiding biases caused by differences in scale.

Let's denote:

X as the original data matrix with dimensions $m \times n$

$\bar{X}$ as the standardized data matrix and Σ as the covariance matrix of X.

λi as the i-th eigenvalue of Σ and vi as the corresponding eigenvector.

Standardization is given by

$$\bar{x}_{ij} = (x_{ij} - \mu_j)/\sigma_j \tag{1}$$

PCA calculates the covariance matrix of standardized data.

$$\Sigma = 1/m \sum_{i=1}^{m} \bar{x}_i \bar{x}^T_i \tag{2}$$

The covariance matrix provides information about how features vary together. It describes the relationships between the dataset's variables.

Next, calculate the eigenvectors and eigenvalues of the covariance matrix. Eigenvectors and eigenvalues represent the data's maximum variance directions and magnitude, respectively. Eigenvectors are principal components.

PCA sorts the eigenvalues in descending order and selects the top k largest eigenvectors. These eigenvectors provide a new foundation for the transformed feature space.

This projection decreases the dimensionality of the data while maintaining as much variance as possible.

Project the standardized data $\bar{X}$ onto the subspace spanned by the selected eigenvectors:

$$Y = \bar{X} Vk \tag{3}$$

CHAPTER 25

Evaluating Ensembles of Machine Learning Models for the Prediction of Smartphone Addiction

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Abstract: In recent years, there has been a truly revolutionary change in the technology behind mobile phones. After being initially used for making phone calls and sending text messages, the pattern of usage has now shifted to include the use of more advanced software (apps) based on platforms like Android and IOS. Because of this, individuals have developed an extreme dependence on their cellphones, and the majority of them are suffering from a condition associated with smartphone addiction. This study examined the ensemble machine learning models' ability to predict smartphone addiction. One hundred people completed a well-designed questionnaire. College students, housewives, merchants, and laborers of all ages participated. Data were used to train ensemble-based machine learning models. Workers and students have higher smartphone addiction rates than other groups. Many ensemble learning models were utilized for prediction and assessment. To evaluate the model's performance, various evaluation measures were used, including Classification Accuracy (CA), Area Under the Curve (AUC), Precision, F1-score, Recall, and Matthews Correlation Coefficient (MCC). With an Area Under the Curve (AUC) of 0.960, a Confidence Interval (CI) of 96.1, and a Mean Aquared Error (MCC) of 0.923, LightBGM displayed the greatest performance among the models that were evaluated. This indicates that it has a stronger predictive potential for determining the degrees of smartphone addiction.

Keywords: Ensemble machine learning, LightBGM, Matthews Correlation Coefficient (MCC), Performance evaluation, Smartphone addiction.

INTRODUCTION

A smartphone's many useful features, including a camera, media player, gaming console, web browser, high-speed internet access, and GPS, make it an integral

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element of our daily life. [1] They have supplanted telephones and serve as a potential solution for laptops, personal computers, and many other devices [2]. Research estimates that by 2021, there will be more than 3.8 billion smartphone users worldwide. There will likely be 829 million users in India by 2022. The frequently updated systems, such as Android and iOS, have user-friendly software (apps) available, which is responsible for the significant rise [3].

The widespread use of smartphones in modern society has raised concerns about the potential for smartphone addiction and its associated consequences [4]. Understanding and predicting levels of smartphone addiction are crucial for implementing effective intervention strategies and promoting healthy technology use behaviors [5, 6]. Machine learning techniques, particularly ensemble models, have become valuable tools for predictive analytics across various domains, including behavioral studies.

The widespread adoption of smartphones has brought about significant societal changes, yet it has also led to concerns regarding Problematic Smartphone Usage (PSU), characterized by overuse injuries and functional impairments [7]. Recent research highlights the prevalence of PSU, with terms like “smartphone addiction” or “smartphone use disorder” being used interchangeably. The KISA survey reveals excessive smartphone usage, particularly among 15-25-year-olds [8]. It seems that many users exhibit addiction-like tendencies, suffer anxiety away from their devices, and struggle to cut down despite efforts [9]. Internet, gaming, and social media addiction damage physical and mental health. Smartphone addiction was assessed and predicted by examining usage behaviors, FOMO, stress, concern, sleep disturbances, social media activity, and physical symptoms such as headaches and wrist pain [10, 11].

EML may predict smartphone addiction, and its application focuses on mental illness analysis accuracy and reliability. To achieve this, the study surveys college students, housewives, entrepreneurs, and workers of various ages. Data from these various groups is used to construct ensembles of machine learning models that effectively predict smartphone addiction. Ensemble machine learning enhances predicted performance by combining multiple models. These methods are ideal for complex issues like smartphone addiction prediction because they utilize multiple models to enhance accuracy and resilience. This research utilizes ensemble machine learning to more accurately predict smartphone addiction across demographic groups. This technique might help understand and treat smartphone addiction, enabling population-specific therapies and support.

This research utilizes survey data to compare ensemble machine learning methods, including AdaBoost, Random Forest, LightGBM, and XGBoost, to identify the most accurate and computationally effective smartphone addiction model. Predictive performance was measured by the area under the curve CA, F1-scoring, Precision, Recall, and MCC. This study aims to develop a smartphone addiction risk model that achieves both accuracy and computational efficiency.

This study contributes to the understanding and addressing of smartphone addiction by identifying effective prediction models, which aid in efforts to reduce addiction and promote healthy smartphone use across various demographics. The chapter covers the basics, optimal machine learning models, results, and conclusions.

FLIGHT FARE PREDICTION USING ENSEMBLE MACHINE LEARNING

This section describes a methodology for constructing an ensemble machine learning prediction model to predict mobile addiction diseases. Fig. (**1**), “Ensembles Machine Learning Techniques for Predicting Smartphone Addiction,” illustrates the data collection, model creation, assessment, and deployment processes.

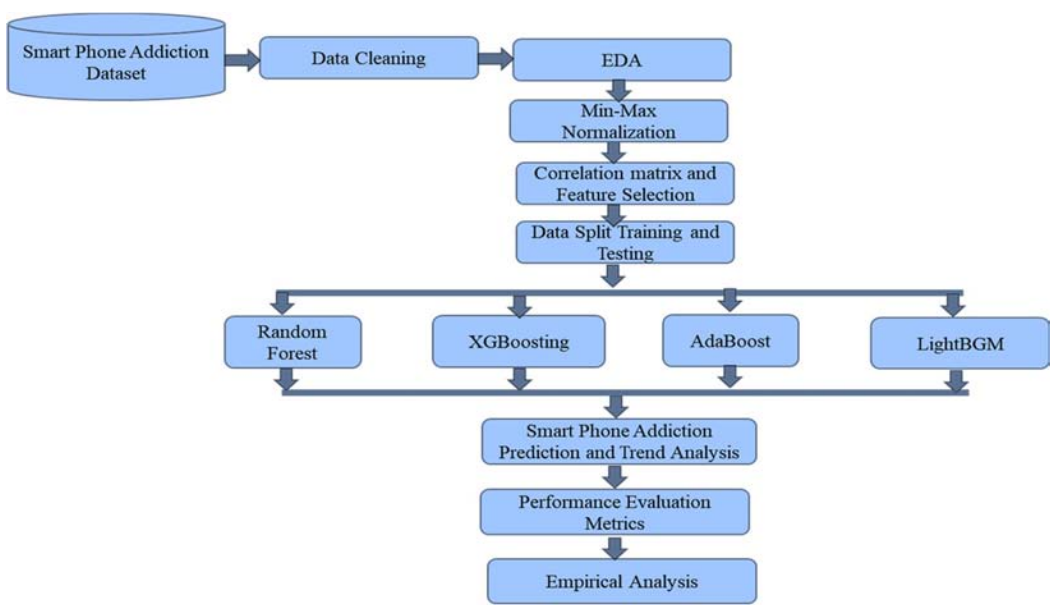

Fig. (1). Ensemble machine learning models for predicting smartphone addiction.

CHAPTER 26

Deep Learning-Based Emotion Recognition System with Depression Detection Capability

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Abstract: This chapter introduces a new approach for automated facial expression analysis in video data to diagnose sadness. The objective is to use sophisticated machine learning to construct a comprehensive facial cue-based emotional assessment system. Face identification algorithms in each frame identify video data after the Extended Cohn-Kanade database preprocesses it for consistency and speed. Time-dependent facial expression characteristics are extracted using Long Short-Term Memory (LSTM) networks and used to build Support Vector Machine (SVM) classifiers. In emotion categorization experiments, an accuracy of 99.19% was achieved. The ratio of positive to negative feelings in video footage measures depression. This chapter proposes the use of automated emotional analysis for early detection and monitoring of depression, utilizing facial expression data.

Keywords: Detection, Depression, Facial emotions, LSTM, Machine Learning, SVM.

INTRODUCTION

The faces show joy, sadness, surprise, and disdain. Expression interpretation is crucial for effective communication, mental health assessments, and social interactions [1]. Multifaceted depression and other emotions are hard to control [2]. Diagnostic and treatment delays are caused by doctors' subjective perceptions in traditional depression diagnosis [3].

Machine learning has revolutionized affective computing by automating facial expression analysis and emotion recognition [4]. Deep learning models, such as LSTM and SVM, can extract significant patterns from complex data, like facial imaging [5]. Large datasets, such as the Extended Cohn-Kanade database, can

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teach these algorithms to recognize facial expressions associated with numerous emotions, including melancholy [6]. Developing effective and accessible depression detection and monitoring tools, particularly for underprivileged populations where early intervention may be critical, drove this effort [7, 8]. We want to construct a robust framework that objectively assesses emotional states and identifies depression using machine learning-based facial expression analysis [9, 10]. This technology may enhance established diagnostic methods by providing a cost-effective and scalable solution for mental health evaluations in both clinical and community settings. We offer a comprehensive system for automated facial expression analysis in video data, with a focus on identifying depression [11]. Facial expressions are crucial to mental health evaluation; however, existing diagnostic approaches have limitations. We next examine how LSTM networks and SVM classifiers can overcome these issues [12].

PROPOSED SYSTEM

This paper introduces an ensemble machine learning model for face emotion recognition.

This model, called SENTINEL (Sequential LSTM and SVM Network for Time-series Learning), is integrated into our proposed system, as shown in Fig. (**1**).

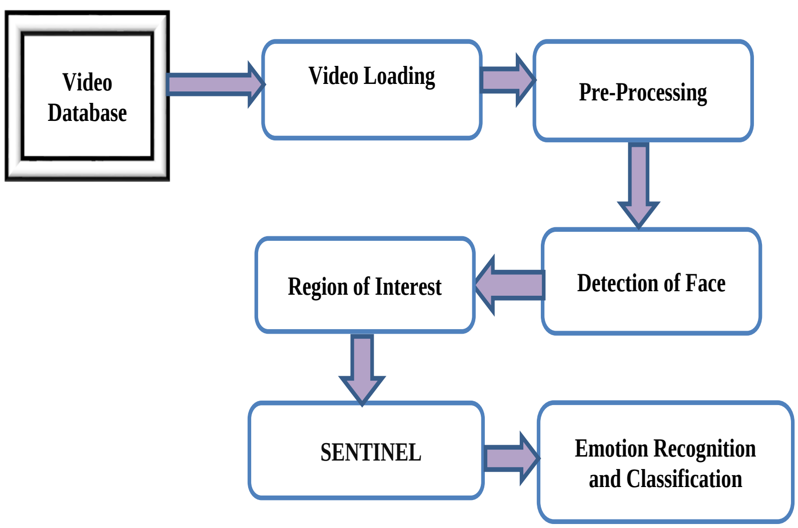

Fig. (1). Block diagram of the proposed system.

Load the video file containing facial expressions V and preprocess the video frames as needed, such as resizing or normalization. Use a face detection algorithm to find faces within each frame. If no faces are detected, handle the situation appropriately. Extract the region of interest (face) from the frame using the detected face bounding box. Use an LSTM model to analyze the temporal dependencies in facial expressions.

LSTM processes a sequence of inputs $\{x1,x2,...,xT\}$ over time and computes a hidden state *ht* at each time step using the following equations:

The input gate is given by

$$i_t = \sigma(Wxixt + Whiht - 1 + bi) \quad \textbf{(1)}$$

Where W represents weight matrices, *b* represents bias vectors, and *ht* is the hidden state at time stamp t.

In addition to the above, other gates and states, represented by the forget gate, cell gate, output gate, and cell state, are also available.

Extract features from either the LSTM output or the facial expression sequences. Train an SVM classifier with the extracted features and emotion labels. The SVM model seeks to find the best hyperplane that separates different classes by maximising the margin. For linearly separable data, the decision function of the SVM can be represented as:

$$f(x) = sign(\boldsymbol{w}_T\boldsymbol{x} + b) \quad \textbf{(2)}$$

Where **w** is the weight vector, **x** is the input feature vector, *b* is the bias term, and sign denotes the sign function.

Proposed Model -SENTINEL

A unique time-series data analysis method for face emotion identification is SENTINEL (Sequential LSTM and SVM Network for Time-series Learning). Time dependency and classification accuracy are improved by SENTINEL, combining LSTM and SVM. LSTM describes the dynamics of sequential data, whereas SVM classifies robustly using derived properties. In practical applications, this hybrid technique enables the analysis of time-series data more accurately and effectively. For temporal applications, such as facial expression detection, SENTINEL's unique LSTM-SVM combination emphasizes sequential learning. By targeting sequential data, SENTINEL identifies temporal patterns

CHAPTER 27

Tackling Environment Unpredictability: A Sensor-Based Approach to Temperature and Humidity Control

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Abstract: In this chapter, the importance of environmental monitoring and the necessary actions related to it areaddressed. For this, environmental parameters such as humidity and temperature are examined and controlled using the Digital Humidity and Temperature sensor (DHT11). After monitoring the latest findings, we regulate the environment's humidity and temperature based on sensor data, making it easier to control the necessary temperature in a theater or auditorium.

Keywords: Arduino (IDE), Microcontroller (Arduino UNO), Sensor (DHT11), Simulation Platform (NI LAB VIEW).

INTRODUCTION

Many technological advances in the modern era have enabled the automated completion of specific activities [1]. The micro controller is one of these innovations that is essential to the intelligent systems of the electronic age [2]. A microcontroller is a single-chip control device that produces precise results and

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enables the automation of desired systems and control processes [3]. A public auditorium is the most significant space and must be maintained at the right temperature among all the spaces it occupies. Today, it's crucial to preserve auditoriums at a pleasant temperature for the health and productivity of everyone, as well as to prevent food, medication, and other goods in the area from spoiling [4]. The manual Air Conditioning (AC) system is often used by people to regulate the temperature in auditoriums [5]. However, this manually controlled equipment has several significant short comings. The drawback is that if the user neglects to switch on or regulate the AC when the temperature becomes abnormal, children, individuals with disabilities, and perishable goods may be injured [6]. Another issue with the mechanical AC system is that, even when the Air Conditioner (AC) is still operational, it may be challenging to maintain the ambient temperature at times. Additionally, if improperly handled, it might lead to wasteful spending and energy use [7]. In general, regardless of the room temperature, activities always require the user to switch it on and off. As a result, environmental monitoring and management are necessary to address these shortcomings [8]. An automatic room temperature control system is a self-contained temperature control system that can adjust the AC level based on the current room temperature. It includes a Microcontroller Unit (MCU), a temperature and humidity sensor (DHT11), an Air conditioner, and National Instruments Laboratory Virtual Instrument Engineering Workbench (NI LabVIEW) to monitor and control the environmental temperature. The microprocessor compresses sensor temperature readings to a pre-defined value based on the ambient temperature [9]. The microcontroller then makes a judgment on compliance [10]. The key advantages of this system are that it is simple to operate, consumes less energy, is cost-effective, allows for more precise temperature control, and is user-friendly.

LITERATURE SURVEY

Humidity is a measure of the quantity of water vapor in the atmosphere. A multitude of chemical, biological, and physical processes are impacted by atmospheric humidity levels. Humidity may also affect public safety and health, as well as product prices for organizations and the general population. Therefore, humidity measurement is critical in the semiconductor and control system industries. A gas's humidity determines how much moisture it contains; a gas might be a mixture of nitrogen, water vapor, pure gas, or argon, for instance. Humidity sensors can be classified into two groups based on their units of measurement. There are two types of humidity sensors: absolute and relative. The DHT11 is a humidity sensor and digital temperature sensor. The DHT 11 is an inexpensive digital sensor that measures humidity and temperature. This sensor instantly calculates humidity and temperature and can be easily interfaced with any microcontroller board, such as the Raspberry Pi or Arduino.

The DHT11 device, as shown in Fig. (**1**), features a thermistor for measuring both capacitive humidity and temperature. Using a moisture-holding substrate as a dielectric, the humidity sensor capacitor includes two electrodes. With a change in humidity levels, the capacitance changes its value. The IC interprets, calculates, and converts the modified resistance values into a digital format.

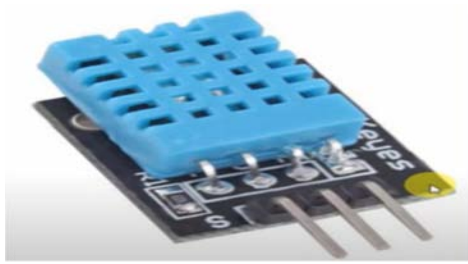

Fig. (1). DHT11sensor.

As the temperature increases, the resistance value drops, indicating that the thermistor used to monitor the temperature has a negative temperature coefficient. Many of these sensors are made of ceramics, polymers, or semiconductors, allowing them to withstand even the slightest temperature changes with a high resistance value. Fig. (**2**) shows that the DHT11 can detect temperatures between 0 °C and 50 °C with a margin of error of 2 °C. The humidity range this sensor covers is 20% to 80%, with a 5% accuracy. This sensor provides a single reading every second, due to its 1 Hz sample rate. The DHT11 requires just three to five volts of power and has a compact design. The highest current allowed during measurement is 2.5 mA.

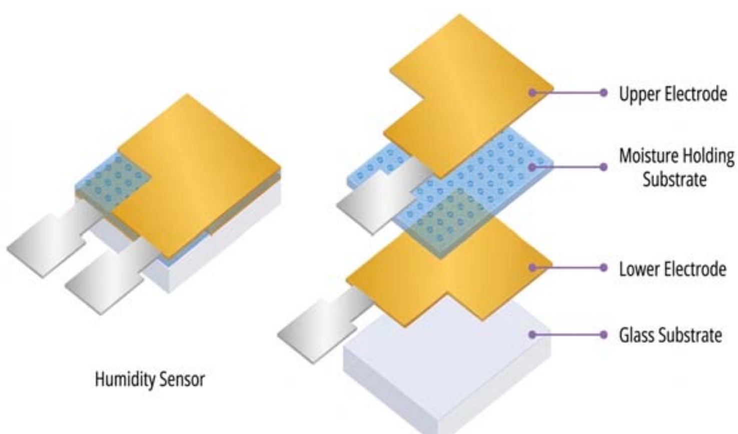

Fig. (2). Inside structure of DHT11 sensor.

CHAPTER 28

Evaluating Ensemble Machine Learning Approaches for Accurate Flight Pricing Predictions

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Abstract: We employ Ensemble Machine Learning to predict airline tickets. The goal is to develop an accurate travel expenditure forecasting system using aircraft trajectories, departure and arrival dates, carriers, and other relevant data. Customers can better plan their holiday budgets and make informed price decisions using the suggested system, which benefits airlines and travel companies. Extended testing measured the model's performance using many measures. Considered factors included Root Mean Squared Error RMSLE, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R2. Extra Trees Regressor outperformed famous ensemble learning models in terms of MAE, RMSE, and R^2. Since Ensemble Machine Learning systems can properly forecast airline rates, this study may affect travel pricing and customer service.

Keywords: Extra tree regressor, Ensemble machine learning, Flight fare prediction, MAE, MSE, RMSE, XGB regressor.

INTRODUCTION

Airline profits and competitiveness depend on accurate flight pricing [1]. Ensemble Machine Learning (EML) employs various strategies to enhance fare prediction [2]. For complex airfare factors, EML may improve generation and reduce overfitting. EML improves airfare accuracy, as our study indicates [3]. EML handles route, length, and time complexity. Successful energy and stock market predictions drive EML application in airline pricing. This research investigates the hypothesis that Ensemble Machine Learning (EML) can accurately predict trip expenses. Many algorithms suggest using EML approaches to identify data patterns [4, 5]. Fuel price volatility, market competition, and

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seasonal variances make airline pricing forecasting difficult. Standard regression and linear models struggle to capture non-linear correlations and complex interdependencies. Gradient boosting, neural networks, decision trees, and random forests solve these difficulties. Ensemble models reduce variation and bias by using predictions from many base learners. An airline price dataset and its components are used to evaluate several EML models [6]. Models include Extra Trees Regressor, Gradient Boosting, eXtreme Gradient Boosting (XGB), and Random Forest (RF). Airline, travel company, and customer pricing, as well as vacation choices, may be improved by a model that balances accuracy and computational efficiency. The primary goal of this study is to predict flight cost accuracy using Ensemble Machine Learning [7]. To inform aviation decision-makers, this chapter compares XGBoost and gradient boosting with single-model methods, and examines the impact of ensemble size and feature engineering on accuracy. To train our novel model, we employ ensemble machine learning techniques on a comprehensive dataset that includes historical trip pricing data [8]. It constructs a reliable model for predicting flight prices, demonstrating efficacy and precision across various performance metrics, including MAE and RMSE. This chapter contributes to the ongoing conversation about how the travel and tourism sector utilizes machine learning by clarifying the role of EML in predicting flight fares. The findings may lead to the development of more nuanced pricing models and strategies [9]. The remainder of the chapter is organized as follows: Section 2 provides a fundamental introduction and relevant literature; Section 3 details the application of the optimal ensemble machine learning model to the dataset used for predicting flight prices [10]. The findings and discussion are presented in Section 4, while Section 5 provides the conclusion.

BASIC PRELIMINARIES AND RELATED WORKS

This section introduces the foundational principles and relevant literature concerning flight price prediction, acknowledging the increasing significance of accurate fare forecasting within the evolving aviation industry for both airlines and travelers. The adoption of Machine Learning (ML) techniques, notably Ensemble Machine Learning (EML), offers a promising solution to the challenges inherent in predicting flight prices with precision. ML algorithms enable the analysis of extensive historical data, facilitating pattern identification and insightful extrapolation to support informed pricing decisions. Notably, Ensemble Machine Learning (EML) has gained prominence for its ability to aggregate predictions from diverse models, thereby enhancing prediction accuracy and robustness.

The chapter presents a predictive model for airline ticket prices, integrating deep learning techniques and social media data to achieve an accuracy rate of 61.9%. Meanwhile, research focuses on machine learning methodologies for fare prediction, analysing various factors, and evaluating algorithm performance. Additionally, details the extraction and integration of diverse attributes for forecasting quarterly average ticket prices, showcasing the model's predictive capability. Proposes a flight fare prediction model using MADA, integrating diverse data dimensions through a seq2seq model with attention mechanisms that employs Logistic Regression (LR), Support Vector Machine (SVM), Multi-Layer Perceptron (MLP)s, XGBoost Tree, and RF models to forecast quarterly average ticket prices, utilizing the Airline Origin and Destination Survey (DB1B) and the Air Carrier Statistics database (T100). The combined dataset, augmented with macroeconomic data, achieves high accuracy by optimising the R-Score value in the testing dataset.

In the Paper, a comprehensive literature review explores prediction models for both patron and airline aspects, revealing a focus on limited features such as historical ticket prices and purchase dates. The chapter delves into four stages that influence flight prices, Aegean Airlines' decision-making, and eight ML models that achieve 87.42% accuracy in ticket price prediction. Additionally, the Paper reviews multi-goal regression techniques and introduces Deep Regressor Stacking (DRS) as a novel approach for enhancing prediction accuracy. The chapter examines the factors that affect airfare price fluctuations and presents a system that helps buyers make informed decisions when purchasing tickets. Lastly, the chapter demonstrates the feasibility of predicting flight prices using historical data, with bagging regression outperforming other ML models in accuracy and speed.

The chapter discusses the use of datasets such as DBIB and T-100 for predicting airfare within market segments. Their use of linear regression, support vector machines, and random forests allows them to attain a high prediction accuracy of 0.869 on the testing dataset. While Classification and Regression Trees (CART) and RF help with decision-making, the SVM regression model fails. Using a variety of machine learning approaches, the authors of the chapter examine the effect of Aegean Airlines' decision-making on flight costs. Outperforming LR and SVM networks, memory models show an 87.42% improvement in accuracy compared to the Packing Regression Tree model. The usefulness of a random forest-based ML model for airline price prediction that uses Kaggle flight cost data to forecast expenditures.

Existing literature emphasizes the crucial role of ensemble learning in precise flight price prediction, given the complexity of the aviation industry. Ensemble

CHAPTER 29

Facial Biometrics for Seamless Attendance Tracking in Educational Institutions

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Abstract: The invention and implementation of a system that makes use of face recognition is the objective of this research project, which aims to automate the management of attendance for educational and industrial organizations. The strategy that has been recommended takes advantage of modern technology to enhance the accuracy and efficiency of the monitoring of attendance. The system is designed to operate in a wide range of environments, including workplaces, educational institutions, and academic institutions. To take and analyze face images in real time, it takes advantage of a Logitech C270 webcam in conjunction with an NVIDIA Jetson Nano development system. To maintain accurate records, administrators and teachers are permitted access to an Excel spreadsheet that contains the attendance data that is gathered and updated on an hourly basis. PCA, which stands for principal component analysis, is used in this approach to provide a condensed representation of facial traits. This results in an increase in the effectiveness of face recognition.

Keywords: Academic institutions, Face recognition, Management of attendance, PCA, Spreadsheet.

INTRODUCTION

Attendance management is crucial for schools, businesses, and organizations to track participation and hold members accountable [1]. Roll call and paper sign-in have always been laborious [2]. Automation, however, uses technology to boost accuracy and production [3]. This initiative uses facial recognition to enhance attendance management in corporations, institutions, and schools. Handwritten

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attendance is tiresome, manipulable, and error-prone. An automated face recognition system may solve these issues and streamline the process. Such technologies improve organizational and educational efficiency and modernity.

The recommended attendance system uses cutting-edge technology and software, including face recognition, for optimal efficiency [4]. It employs a Logitech camera and an NVIDIA Jetson Nano development kit to capture and analyze facial photos in real time. This arrangement offers high-quality images and fast processing, making it essential for precise attendance tracking. These algorithms enable the system to detect faces accurately, regardless of angle or light. Combining these tactics enables the system to reliably recognize individuals and retrieve their data from the database [5].

Using a face recognition attendance system, both students and faculty feed their names, roll numbers, class information, and photographs [6, 7]. A reliable attendance record may be created by training the system to discriminate between specific faces and persons. Accurate identification and attendance in the system during operation are ensured by training user-friendly facial recognition attendance system. The computer takes a face shot to contrast with the training information when people visit pre-arranged locations. Automatic attendance recording follows successful identification, eliminating the need for human contact. This streamlined process enhances attendance management efficiency and saves time [8].

Attendance is updated hourly in an Excel file for administrative and record-keeping purposes. Teachers and administrators may collect and analyze attendance data on this sheet [9]. Principal Component Analysis (PCA) compacts facial information to enhance face recognition. The invention and implementation of a face recognition-based attendance system are crucial to upgrading attendance management in enterprises, workplaces, and schools. Technology solves manual attendance tracking problems in a reliable, accurate, and effective manner [10]. This study aims to enhance attendance management approaches, leading to a higher level of effectiveness in many scenarios.

LITERATURE SURVEY

Research on attendance management has largely focused on automating and increasing productivity through the use of technology. Research has examined fingerprint, iris, and facial recognition for attendance monitoring in companies and schools. Biometric-based attendance systems are popular because they can consistently identify individuals and prevent proxy attendance. Studies have indicated that the use of biometric techniques in attendance control can improve security and accountability. Numerous studies have compared variables, including accuracy, dependability, and user acceptability, to assess how well various biometric modalities perform in practical contexts. Facial recognition technology has become a viable alternative to fingerprint recognition systems, owing to its non-intrusive nature and simplicity of implementation.

Bussa *et al*. proposed an OpenCV-based facial recognition methodology for recording attendance in businesses. It takes pictures with a camera for input, recognizes faces using an algorithm, and stores cropped photos with labels in a training database. The LBPH algorithm is used to extract the features, which makes the conventional approaches laborious and time-consuming. Khan *et al*. note that tracking college attendance has always been a laborious process. The existing biometric attendance system, however, needs a line to scan fingerprints and is not automated. In this research, a system utilizing smartphones and well-known object detection algorithms, such as Microsoft Azure's face API for facial recognition and YOLO V3 for face detection, is proposed. To verify that pupils are present in class, a special camera takes two photographs in the classroom. The system detects faces with great precision and operates effectively in real time. Gupta *et al*., through the use of open computer vision and face identification and recognition, created the Student Attendance mainframe structure is a system created to enhance conventional university attendance systems. The goals of this system are to decrease long-term work and disposables, enhance flexibility, and save time and money. The system uses Python to create automated documents or spreadsheets, compute present and absentee figures, and take attendance notes.

Algorithm invention, hardware integration, and user interface design have been studied in facial recognition-based attendance systems. LBPH, Eigenface, as well as Fisher Face have been studied for dependable and accurate face identification in many situations. Facial recognition systems have been tested in companies, public spaces, and schools. Analyzing lighting, camera angles, and facial expressions, researchers evaluated the system's performance and found flaws. User acceptance and privacy have been widely studied in face recognition attendance systems. Privacy and open data management are vital, according to a study on managers, workers, and students' views on biometric technologies.

For school attendance, Suresh *et al*. plan to employ face recognition. Face-based identification lowers divergence and duplication. Face databases will aid the recognition method, which compares faces throughout attendance sessions. It automatically records and sends the indicated students' attendance to the relevant faculty member in Excel. Kiran *et al*. used Face Recognition (HFR) for user authentication in network security, smartphone access control, and surveillance systems. This study introduces an HFR-based classroom attendance system. A

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