ADVANCED MACHINE LEARNING For complex medical data Analysis

Editors: Saumendra Kumar Mohapatra Mihir Narayan Mohanty Rashmita Khilar

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Advanced Machine Learning for Complex Medical Data Analysis

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FOREWORD

In the ever-evolving landscape of healthcare, the fusion of advanced machine learning and medical data analysis stands as a beacon of innovation and promise. As we navigate the complexities of a data-rich era, the book you hold in your hands, "Advanced Machine Learning for Complex Medical Data Analysis," emerges as a timely and indispensable guide to the forefront of this transformative intersection.

As our understanding of medical science deepens, so does our ability to harness the potential of machine learning algorithms. This edited volume, curated by Mihir Narayan Mohanty, Rashmita Khilar, and Saumendra Kumar Mohapatra and a cadre of esteemed contributors, brings together a tapestry of insights, methodologies, and breakthroughs that collectively define the state of the art in medical data analysis.

The chapters contained within these pages span the spectrum of applications, from predictive modelling that foretells patient outcomes to the nuanced intricacies of personalized medicine. The authors, each an expert in their field, share not only their successes but also the challenges and ethical considerations that accompany the integration of advanced machine learning into the fabric of healthcare.

What makes this volume truly exceptional is its ability to balance the theoretical underpinnings of machine learning with the practical implications for medical practitioners, researchers, and technologists. As we embark on a journey through these chapters, we are guided not only by the intricacies of algorithms but also by a commitment to improving patient outcomes, streamlining healthcare workflows, and enhancing the overall efficacy of medical decision-making.

To the readers, I encourage you to approach this book with a sense of curiosity and anticipation. The insights contained herein have the potential to shape the future of healthcare delivery, making it more precise, personalized, and responsive to the needs of individual patients and populations at large.

I extend my heartfelt congratulations to the editors and the contributors for their dedication to advancing the field. May this volume serve as a catalyst for continued exploration, collaboration, and innovation at the nexus of machine learning and medical data analysis.

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PREFACE

Welcome to "Advanced Machine Learning for Complex Medical Data Analysis." In this edited volume, we bring together a diverse collection of experts and practitioners at the intersection of machine learning and medical research to explore the cutting edge of datadriven solutions in the field of healthcare.

The landscape of medical data analysis is rapidly evolving, and the integration of advanced machine-learning techniques is revolutionizing the way we approach complex medical challenges. As the editors of this compilation, our goal has been to assemble a comprehensive array of contributions that showcase the latest methodologies, innovations, and applications in the realm of medical data analysis.

This volume is organized into thematic sections, each dedicated to a specific aspect of advanced machine learning in the context of medical data. From predictive modeling and diagnostic tools to personalized medicine and data security, our contributors delve into the intricacies of applying machine learning algorithms to solve real-world problems in healthcare.

We would like to express our gratitude to the esteemed authors who have contributed their expertise to this volume. Their insights and dedication have been instrumental in creating a resource that bridges the gap between theoretical advancements in machine learning and the practical demands of medical data analysis.

This book is designed for researchers, practitioners, and students who are passionate about leveraging the power of machine learning to address the complexities of medical data. Whether you are a seasoned expert or a newcomer to the field, we believe that the diverse perspectives presented here will inspire and inform your work.

We hope you find "Advanced Machine Learning for Complex Medical Data Analysis" to be a valuable resource and a source of inspiration for your explorations into the fascinating intersection of machine learning and healthcare.

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Computational Intelligence Approaches to Predictive Modeling in Clinical Dataset Issues and Challenges: A Review

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Abstract: Predictive modeling in clinical datasets presupposes the expansion of the computational system with the capability to analyze a massive amount of medical data to predict the outcome of every patient. Computational intelligence-based expert systems are acceptable for the analysis of complex data to process it fast and accurately as compared to conventional statistical methods. So the motivation to work with clinical datasets, characteristics like complexity, uncertainty, and imprecision, an advanced predictive model should be developed. This chapter provides a rigorous literature review of recent work on computational intelligence approaches applied to the clinical dataset using predictive modeling. Precisely this chapter's objective is concentrated only on those predictive computational intelligence approaches suitable for handling various characteristics and challenges in a clinical dataset like everchanging data, fragmented data, interdependency among data, poor quality data, colossal volume and heterogeneity, and inaccessible data. Here exploration is done based on the prediction accuracy of a few computational intelligence approaches like Artificial Neural Networks, Deep Learning, Decision Trees, Support Vector Machines, Fuzzy based methods, as well as Bayesian approaches over many clinical datasets, especially breast cancer and its nature and suitability to work with clinical datasets are pointed out.

Keywords: Artificial Neural networks, Bayesian approaches, Breast cancer, Computational Intelligence, Clinical datasets, Decision Trees, Deep learning, Fuzzy techniques, Genetic algorithms, Predictive modeling, Support vector machines.

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INTRODUCTION

In today's digital world, data is all around but then also information lags and knowledge drops; so to do magic with this colossal data, there are various techniques and tools; among these is predictive modeling which is a groundbreaking way to leverage the hidden information to take an appropriate decision from a large number of data set. The colossal collections of electronic healthcare repositories are increasing the chances of developing an expert clinical decision support system that medical experts can use to enhance the patient's health care. The salient challenges for medical experts are diagnosing diseases, assessing risk, and evolving appropriate methods for prediction and final results. The goal of predictive modeling in health care necessitates advancing computational models with the strong capability of predicting future healthcare outcomes [1]. Statistical methods and computational intelligence can improve a new clinical decision support system using a new paradigm. The approaches of computational intelligence amalgamate metaheuristic optimization algorithms, such as Genetic algorithms and fuzzy logic, with machine learning algorithms, such as Artificial Neural Networks, Bayesian Models, and Deep Learning. Predictive modeling has a prime role in machine learning algorithms in which a model is built using existing datasets to make decisions on new patient data, such as a predictive model can be constructed to predict breast cancer using sets of input datasets with clinical results. Once the model is trained using the learning process and tested on standard datasets, the model is ready to receive new cases and predict clinical outcomes.

Computational intelligence approaches can tackle the potential to handle imprecision and uncertainty, which is entirely possible in the clinical dataset [2]. These approaches also work perfectly with a large and complex clinical dataset. Computational intelligence algorithms have been proposed to build predictive models, for example, prostate cancer [1], cardiovascular disease [3 - 5], lung cancer [6], diabetes [7, 8], and Alzheimer's disease [9].

This survey chapter discusses recent research on various clinical datasets like heart disease, chronic kidney disease, prostate cancer, lung cancer, and diabetes but rigorously reviewed papers on breast cancer predictive modeling using computational intelligence approaches. Breast cancer increases at an unpredictable rate, making it the most common and scary cancer in women [10, 11].

SIGNIFICANCE OF PREDICTIVE MODELING IN THE CLINICAL CARE INTELLIGENCE

Predictive modeling is the primary area of interest to all research communities and organizations. The massive availability of lots of new computational techniques and tools for predictive modeling assists researchers and practitioners in selecting the most appropriate strategy. Predictive analysis has become a noteworthy spectrum for researchers and practitioners in the clinical world. The following describes the significance of healthcare predictive analytics for healthcare providers, as shown in Fig. (1).



Fig. (1). Benefits of predictive modeling in clinical care.

Improved Diagnostics

The predictive modeling system is beneficial in clinical decision-making. Few diseases have prototypical symptoms that can be easily identified and cured by qualified doctors according to the predefined treatment plan. But in some cases, patients have unconventional signs that point to a particular disease, making diagnostics more intricate. So, predictive modeling aims to derive new models for complex problems that can use lab testing details and diagnostic procedures to predict the outcome of interest. Thus, predictive analytics acquire a magnificent place in the treatment and diagnosis process.

Sky-High Price Effectiveness

Healthcare organizations implement a predictive model so that it can reduce costs significantly. Detailed information on cost management and patient risks can be generated, including a significant amount of accessible statistics on patients, employees, types of equipment, and planning.

CHAPTER 2

Fractional Diffusion Equation for Image Denoising Utilizing C-N-R Approximation Scheme

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Abstract: Denoising images is a crucial aspect of image processing, and the current trend in image denoising involves the rapid development of Riesz fractional order derivatives. In this research, we introduce an abstraction of fractional calculus and a denoising model that relies on the space fractional order diffusion equation. This is achieved through a combination of Crank-Nicolson and Riesz (C-N-R) approximations. We obtain a model that is unconditionally stable and convergent. The model's performance is assessed using visible conception and visual quality assessments, including peak signal-to-noise ratio (PSNR). The results of the observations demonstrate that the achieved enhancements align well with those of others.

Keywords: Crank-Nicolson scheme, Fractional calculus, Fractional Riesz operator, Image denoising.

INTRODUCTION

Image denoising is a fundamental challenge in the field of image processing, with applications across various domains, including medical imaging, photography, and satellite imagery. The presence of noise in digital images can severely degrade the quality and reliability of subsequent image-processing tasks, such as segmentation, enhancement, and analysis. In particular, additive Gaussian noise and speckle noise, which often arise during the acquisition or transmission of images, pose significant challenges in preserving image details while reducing noise.

Traditional denoising techniques such as Gaussian filters, Kuan filters, and Wiener filters have been widely used to mitigate noise. However, these methods often face limitations in preserving important image features like edges and textures, leading to a compromise between noise removal and detail preservation.

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Fractional Diffusion Equation

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In recent years, fractional calculus has gained attention for its ability to model complex systems, including image denoising. Specifically, fractional-order derivatives offer a more flexible and accurate approach to describing image structures. This research introduces a novel Crank-Nicolson and Riesz (C-N-R) approximation scheme for space fractional order diffusion equations, aimed at enhancing image denoising performance. The proposed model demonstrates unconditional stability and convergence, and it is particularly effective in preserving the intricate details of images while significantly reducing noise.

Related Work

Fractional integration and differentiation have found application in diverse physical phenomena, encompassing diffusion, control engineering theory, oscillation behaviours, solid mechanics, astrophysics, viscoelasticity, neural computing, biomedical applications, signal processing, and image processing. Recently, the derivative of fractional order has been paid significant attention in engineering sciences. Research on fractional order partial differential equations [1 - 4] featuring various operators like Riemann-Liouville, Erd'elyi-Kober, Weyl-Riesz, Caputo, and Gr^unwald-Letnikov has progressed over the past four decades and has expanded into other fields.

Noise is described as an unwanted feature that may contaminate an image. The process of removing noise from a captured image is referred to as image denoising, and it is essential for subsequent image processing tasks, including segmentation and texture analysis. Image denoising in the fractional domain has gained serious research attention. Many fractional derivatives based algorithms [5, 6, 8] have been proposed for image denoising. Meerschaert and Tadjeran [22] derived the shifted Gr^unwald-Letnikov formula for the approximation of flow equations incorporating fractional advection and dispersion. Furthermore, Meerschaert and Tadjeran [16] have devised an approach for resolving bidirectional spatial fractional order partial differential equations through discretized difference approximations. Pu et al. [20] outlined essential features of the Grünwald-Letnikov fractional derivative approximation scheme, characterized by an order of O(h), suitable for numerical simulations. Abirami et al. [1] explored the application of the CN-GL scheme to the Rudin Osher Fatemi (ROF) model with a fractional diffusion equation, aiming to denoise images across all categories while preserving texture qualities [9-12].

The Riesz operator of the second order is employed for image enhancement and sharpening. Yu *et al.* [24] introduced a crucial fractional algorithm known as the Centered difference of varying fractional order, which relies on the Riesz second-order fractional derivative. The application of this model is suitable for medical

practice and monitoring purposes. Liu and Zhang [25] utilized an implicit discretization method incorporating the Grünwald-Letnikov differential approximation to address a nonlinear diffusion equation involving Riesz fractional derivatives, establishing the approach's stability over a brief duration. Furthermore, Otrigueira [17] introduced the fractional-centered derivative and demonstrated its ability to represent an analytic function under Riesz fractional differential transformation. This current study suggests a straightforward and efficient method for image denoising, employing the Riesz fractional derivative and the Crank-Nicolson scheme in the context of the space-fractional diffusion expression [13-16].

The composition of this research is outlined as follows: Section 2 provides the definitions related to the Riesz fractional-order derivative. Section 3 discusses the implementation of the Crank-Nicolson procedure and the Riesz differential operator. Section 4 presents the stability and convergence analysis of the proposed model, and Section 5 offers experimental results and comparisons with standard methods. Finally, Section 6 concludes the paper with key findings and future directions.

Riesz Type Fractional Differential Operator

Within this research, our team utilizes the Riesz differential operator, as defined below:

$${}_{\mathsf{R}}^{\ \alpha}u(t)=\frac{1}{2cos(\frac{\alpha\pi}{2})\Gamma(1-\alpha)}\frac{d}{dt}\int_{-\infty}^{\infty}\frac{u(s)}{(t-s)^{\alpha-1}}ds,$$

For $\alpha > -1$, the formulation of the fractional-centered difference is established as

$$\Delta_h^{\alpha} u(x) = \sum_{n=-\infty}^{\infty} \frac{(-1)^n \Gamma(\alpha+1)}{\Gamma(\frac{\alpha}{2}-n+1)\Gamma(\frac{\alpha}{2}+n+1)} u(x-nh),$$

and it is shown that,

$$h \xrightarrow{lt} 0 \frac{\Delta_h^{\alpha} u(x)}{h^{\alpha}} = h \xrightarrow{lt} 0 \frac{1}{h^{\alpha}} \sum_{n=-\infty}^{\infty} \frac{(-1)^n \Gamma(\alpha+1)}{\Gamma(\frac{\alpha}{2}-n+1)\Gamma(\frac{\alpha}{2}+n+1)} u(x-nh)$$

represents the Riesz derivation for $1 < \alpha \le 2$. For two variables x and y, the following forms are applicable (in the negative direction).

Revolutionizing Medical Imaging: The Transformative Role of Generative Adversarial Networks (GANs)

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Abstract: Recently different deep-learning algorithms have emerged. But the one that is most promising in medical imaging is the Generative Adversarial Network. In the artificial intelligence field, GANs represent a significant area of research due to their extensive capacity to generate sophisticated data, which has garnered significant attention. The GAN comprises two key deep networks: a generator and a discriminator. The discriminator's role is to distinguish between real images and synthetic images produced by the generator. GANs are typically utilized in medical imaging for two distinct functions. Primarily, the generative component is the focus of attention, since it can help in learning about a generation of new images as well as analyzing and exposing the fundamental framework of the training data. This GAN feature highlights the confidentiality of patient records and also reduces the scarcity of medical data. Secondarily, the discriminative component is the focus of attention in which the aberrant images are provided to the discriminator D, which serves as a detector because it can be thought of as a learned reference for normal images. This chapter focuses on the contemporary evolutions in generative models, especially in the arena of medicine. This article presents the various medical imaging techniques employed in different GAN architectures and the uses of GAN in medical imaging. This article's goal is to give an in-depth comprehension of the GAN and its different architectures and applications of GAN in medical imaging.

Keywords: Adversarial autoencoder (AAE), Auto-context model (ACM), Computed tomography (CT), Convolutional neural network (CNN), Earth mover (ME), Functional near-infrared spectroscopy (fNIRS), Generative adversarial networks (GANs), Intravascular US simulation (IVUS), Jensen-shannon (JS) divergence, Magnetic resonance imaging (MRI), Medical image analysis (MIA), Pixel 2 pixel generative network (Pix2Pix-GAN).

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INTRODUCTION

Medical imaging is very essential in generating exceptional medical images of almost every visceral organ including the kidneys, lungs, brain, heart, bones, and soft tissues. For more than a century, medical imaging has been a critical auxiliary tool in the diagnosis of disorders in humans [1]. The utilization of computer-aided diagnostic techniques has significantly enhanced radiological workflow efficiency through the acquisition of knowledge from medical images. A variety of medical imaging techniques, such as computed tomography, positron emission tomography, magnetic resonance imaging, and ultrasound imaging utilize diverse methods to capture images. Each imaging modality has a different set of fundamental ideas for the acquisition of medical images, data manipulation, and solving complexities. For instance, the dimensionality and complexity of images vary from one another, since it has to incorporate information specific to a particular modality. This leads to improving the process of diagnosis. On the other hand, these differences provide a significant impediment in the synthesis of images across different modalities. Hybrid medical imaging integrates images from two different modalities at the same time, such as CT/PET and MRI/PET imaging. It is a hard task to extract information in hybrid medical imaging that corresponds to one modality. Medical images must fulfill specific requirements, such as superior quality images and maintained features at both low and high levels, in order for automated analysis to be performed on them. By doing away with the requirement for the patient to be scanned multimodally and saving time and money, a framework that translates images between modalities can be very promising. One such unsupervised framework, the Generative Adversarial Network (GAN), has achieved notable accuracy and reliability in cross-modality picture synthesis. Recent advances in machine learning have accelerated the field's growth by outperforming more conventional methods, particularly in Deep Learning (DL) neural networks [2]. The feature maps extracted from deep learning models of medical images, acquired by computed tomography, magnetic resonance imaging, positron emission tomography, mammography, ultrasound imaging, and histology present relevant data needed for medical image analysis [3 - 5]. Deep Learning networks offer cutting-edge methods for tasks in medical image analysis, including image identification, segmentation, and classification. [6 - 8]. The field of medical image processing primarily focused on guided learning with little emphasis placed on the use of generative tasks. This scenario has been changed radically due to the development of Generative Adversarial Networks (GANs) [9]. GANs serve as an intermediate between supervised learning and medical image generation. Due to the advancement in the high dimensional latent distribution of data, GANs improve performance by maximizing the probability density across the distribution that generates the data. GANs achieve their success primarily in contrast to conventional deep learning

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algorithms. It shows exemplary performance in the absence of annotated data. Additionally, the adversarial networks present in GANs are utilized to augment the available dataset, thereby resolving issues related to robustness, which arise due to insufficient data. Lastly, the construction of a GAN follows the confrontation learning process because it consists of a discriminator and a generator.

GANS IN THE MEDICAL DOMAIN

This section explains the general idea underlying GANs and their conditional versions such as deep convolutional generative adversarial networks, markovian generative adversarial networks, conditional generative adversarial networks, cycle generative adversarial networks, auxiliary classifier generative adversarial networks, Wasserstein-generative adversarial network and least squares generative adversarial network, which are among the various GAN variations that are utilized as inspirational models in medical applications. One of the more recent methods for creating "generative models" that use an adaptable self-organizing deep learning model is the Generative Networks. The generative model plays a vital role by employing unsupervised learning to autonomously recognize patterns within the input data. This enables the generation of new instances of data that ally with the uniqueness present in the original dataset. GAN is more well-liked and practical in generating real-time images.

GANs comprise two basic networks *viz.*, a generator that acquires the ability to produce real image data as shown in Fig. (1). The discriminator discriminates real image data from the fake image data generated by the generator. Upon initiating the learning process, the generator generates fictitious data, which the discriminator rapidly becomes adept at identifying as fake. The generator can generate output that can deceive the discriminator while it is being trained. Ultimately, the discriminator is able to discern between the true and fake data assuming generator training is successful. The generator as well as the discriminator uses the neural networks. The output of the generator is directly linked to the input of the discriminator. The signal produced by the backpropagation process of the discriminator's classification task is used to update the weights of the generator network.

GAN Variants

Basic GAN

The fundamental notion of GAN stems from the game theory concept of Nash equilibrium. The GAN is made of two neural networks namely the Generator (G) and the Discriminator (D). By figuring out the distribution of the sample data, the

Big Data in Health Care: Opportunities, Challenges and Future Direction

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Abstract: Today, we find ourselves in a scenario where we are constantly bombarded with data from every aspect of our lives, including social interactions, science, our jobs, our health, etc. It is possible to compare the current state to a data flood. We now produce volumes of data that are beyond the capacity of the currently available technology thanks to technological advancements. As a consequence, the phrase "big data" was coined to refer to vast quantities of meaningless data. We must create new methods for organising data in order to extract valuable information from any of this data and meet both present-day and societal demands in the future. Healthcare is one such specific societal demand. Healthcare firms produce knowledge at a high rate, which presents both a number of benefits and difficulties. This is common in many industries. The fundamental data concepts, their organization, analysis, and possible applications—particularly in the healthcare industry—are covered in this chapter. People working for various governments worldwide produce enormous amounts of data every day. The phrase "digital universe" describes the volumes of data created, copied, and consumed annually. Intercontinental Data Corporation (IDC) estimated the digital universe's unbalanced size to be 130 Exabytes (EB) in 2005. In 2017, the size of the digital world reached around 16,000 EB (16 zettabytes) (ZB). By 2020, IDC predicted that the digital world would reach 40,000 EB. We need to give each entity a data allocation of around 5200 gigabytes (GB) to see this scale.

Keywords: Big data, Digital universe, Healthcare, Healthcare industry, Intercontinental data corporation.

INTRODUCTION

The key to a proper organization and novel setup has always been intelligence. With superior information, we can work together more effectively to get the finest outcomes. Data collection is crucial for all firms as a result. In many different situations, this data can be used to forecast future trends and events. We have just been producing and gathering more data on nearly all of hat by implementing

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data centers in this direction as we become more aware of this. We today find ourselves in a scenario where we are constantly bombarded with data from every aspect of our lives, including social interactions, science, our jobs, our health, etc. It is possible to compare the current state to a data flood. We now produce volumes of data that are beyond the capacity of the currently available technology thanks to technological advancements. As a consequence, the phrase "big data" was coined to refer to vast quantities of meaningless data. We must create new methods for organising data in order to extract valuable information from any of this data and meet both present-day and societal demands in the future. Healthcare is one such specific societal demand. Healthcare firms produce knowledge at a high rate, which presents both a number of benefits and difficulties. This is common in many industries. The fundamental data concepts, their organization, analysis, and possible applications-particularly in the healthcare industry-are covered in this chapter. We are surrounded by big data, but this hasn't changed how we live [1]. It is claimed that as technology advances swiftly, healthcare is going through a "Gutenberg epoch" and a revolution akin to the one that the printing press' invention sparked. Topol suggests that genome sequencing may soon become a normal practice by citing the fact that the cost of sequencing a whole gene has decreased by a fraction of a trillion in the past 15 years. Smartphones resemble a little piece of medical equipment due to their quick monitoring and analytics capabilities. As a result of these technological advancements, healthcare will become more decentralised and doctors won't be necessary [2]. This chapter looks at the opportunities and challenges of this transformation. Better patient outcomes could result from these improvements, which would greatly enhance our quality of life. Patient outcomes include the effectiveness of a patient's sickness medication as well as the results of medical care, including lifespan, morbidity, and cost. Since every human behaviour, including theatre attendance and customer satisfaction, can be tracked, many other businesses may also use this creative method of evaluating healthcare performance. It is challenging to predict patient outcomes since treatments may have positive or negative effects. A painkiller may totally alleviate the discomfort of a hangover, but managing, let alone curing, a complex illness like diabetes is considerably more difficult. The so-called doctor birth outcomes (PROMs), which are evaluations of activity and wellbeing as described by patients, have been rigorously collected by healthcare professionals [3].

How Big is Big Data

People working for various governments worldwide produce enormous amounts of data every day. The phrase "digital universe" describes the volumes of data created, copied, and consumed annually. Intercontinental Data Corporation (IDC) estimated the digital universe's unbalanced size to be 130 Exabytes (EB) in 2005.

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In 2017, the size of the digital world reached around 16,000 EB (16 zettabytes) (ZB). By 2020, IDC predicted that the digital world would reach 40,000 EB. We need to give each entity a data allocation of around 5200 gigabytes (GB) to see this scale. It illustrates the astonishing rate of expansion of the digital realm. Internet behemoths like Facebook and Google have been gathering and storing vast data. Google may save several user-related data for future reference, depending on our favorites, including the user's location, billboard preferences, list of submitted materials, computer internet history, contacts, caches, emails, and other relevant data. Similarly, Facebook keeps and analyses more user-generated data than 30 petabytes (PB) [4]. Big data is designed for such vast volumes of data. The IT sector has recently utilized big data to provide vital information that may earn significant revenue. These findings have drawn so much attention that a new branch of research known as "Data Science" has finally emerged. Data administration and analysis are just two components that data science deals with to gain deeper insights for enhancing a system's operation or offerings (for example, healthcare and transport systems).

Furthermore, it is now simpler to comprehend the workings of any complicated system thanks to the availability of some of the most innovative and expressive techniques to visualize large data post-analysis. It has become necessary to describe big data since a significant portion of civilization is becoming aware of it and finding it challenging to generate. We thus give information on the influence of big data on the transformation of the global healthcare sector and its impact on our day-to-day lives in this study.

Biomedical Data about Big Data

Healthcare is a multifaceted system that aims to prevent, identify, and treat human weakness or health-related problems. Health professionals (surgeons or hospitals), healthcare facilities (clinics, healthcare facilities for delivering medications and other analyses or conducting technology), and a financing institution secondary to the first two are the main processes of a healthcare system. Health professionals work in a range of fields related to health, including dentistry, pharmacy, obstetrics, nursing, psychology, and physiotherapy, among others. Depending on the severity of the ailment, Healthcare is required on several levels. Experts use it as the starting point for discussions on primary care, acute care requiring experienced experts, tertiary care, and highly uncommon diagnostic or clinical treatments (quaternary care).

Health professionals are responsible for various information, including health records (analysis and preparations related data), specialized medical data (such as data from imaging and test checks), and other private or public medical

Applications of IoT in Biomedical Engineering

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Abstract: Biomedical systems including healthcare, diagnosis, prevention, treatment, and monitoring leverage IoT-based biomedical applications. Additionally, research in the field of healthcare is increasingly focusing on individualised measurement. Assessments that are more thorough must take the role of observed assessments in the lab or clinic. However, historically, expensive and complicated equipment has been a barrier to long-term free-lived evaluation. Environmental analysis is required to contextualise individual measurements in free-living evaluations because there are no supervised circumstances present. Biomedical engineers should understand the potential, difficulties, and restrictions posed by inexpensive and widely available Internet of Things (IoT) technology. The use of advanced technologies like Artificial Intelligence, Machine Learning and IoT makes medical science more advanced and its a good impact on human lives.

The Internet of Things (IoT) future roadmap may be conceptualised in terms of the significant technological advancements occurring in the different IoT stack levels. New technologies are presently being rapidly adopted in a wide range of applications in the device sector. Intelligent meetings are real-time conversations that make use of advanced video conferencing systems for remote medical professionals and physicians as well as patients who want to be "up close and personal." Non-intuitive counselling in this context refers to a non-live interview in which the specialists focus on the review information and other patient data that has been transmitted through the system. Furthermore, by sharing the case history and diagnosis, various doctors can transcend the limitations of geography. Many advanced treatments of crucial and critical diseases are possible with advanced biomedical equipment with all technological help. Doctors are able to advance the tracking and treatment of many diseases using biomedical instruments.

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Keywords: Biomedical engineering, Bioinstrumentation, Data acquisition, IoT technology, Sensors, Transducers.

INTRODUCTION TO THE USE OF IOT TECHNOLOGIES IN BIOMEDICAL

The Internet of Things (IoT) has several uses in medicine, including intelligent sensors, medical equipment, and remote observation. It can raise the standard of care while also safeguarding and monitoring patients. By enabling patients to spend more time with their doctors, medical IoT can also assist in improved care. Medical IoT is not without its disadvantages, either. The IT department of a medical facility may have trouble managing the sheer volume of medical equipment and data it generates. Additionally, there is the problem of how to protect patient data, especially when it is moved between several devices. The numerous IoT applications in healthcare and related industries are under research in today's era [1].

The Internet of Things' (IoT) future roadmap can be conceptualised in terms of the significant technological advancements occurring in the various IoT stack layers. New technologies are currently being rapidly adopted in a wide range of applications in the device sector. Intelligent meetings are real-time conversations that make use of advanced video conferencing systems for remote medical professionals and doctors as well as patients who want to be "up close and personal." Non-intuitive counselling in this context refers to a non-live interview in which the specialists focus on the review information and other patient data that has been transmitted through the system. Furthermore, by sharing the case history and diagnosis, various doctors can transcend the limitations of geography [2]. The Internet of Things (IoT) is rapidly integrating into some sectors, but some industries, such as healthcare, are much slower to integrate IoT [3]. IoTM (IoT for Medical) imagines a collection of wirelessly enabled healthcare devices and people to enable the sharing of medical data, eliminate patient surveillance, and ultimately improve patients' quality of life. IoTM can not only improve the quality of people's lives but also play a role in enhancing healthcare services and providing hospitals at affordable healthcare costs. IoTM implementations in healthcare are growing exponentially around the world, but there are still some challenges that require to be solved to increase execution. Scalability, mobility, cost, complexity, management, trust, security, and interoperability are just a few of the issues preventing the use of IoT technology in the healthcare sector [4].

Interoperability and security appear to be major concerns for IoTM. IoTM consists of three parts [5].

Applications of IoT

- Biomedical devices for collection of data.
- Different methods of connecting data with the internet cloud.
- Software for data processing, protection, transmission and display.

It is important to take these into consideration to ensure device functionality. Fortunately, various areas of healthcare, which often revolve around the commercial-oriented side of IoT, are proliferating. Wearable health devices also have many limitations, such as: Government regulations and approvals delay the device's introduction to the market and increase the risk for investors. They are getting smaller, which inevitably makes it harder to compete with real medical devices [6]. Furthermore, before any human testing can be performed (even on a prototype), rigorous and cumbersome criteria must be established [7, 8].

Despite these drawbacks, IoTM has many advantages. As healthcare is an increasingly stressful industry today, the need for long-term care will continue to increase [9 - 11].

IoTM can provide:

- Home monitoring services that reduce healthcare costs with the benefits of automation.
- Health and wellness services that keep seniors working longer.

Study finds reducing patient healthcare costs by streamlining and discussing general health information, using medical IoT to manage chronic health conditions, and monitoring routine check-ups *via* IoT savings have been suggested [12].

A very important advantage of medical IoT is its efficiency. This allows us to solve some of the most difficult problems in healthcare. Access to the appropriate information in a situation that is very dynamic and enhanced patient satisfaction by directing medical professionals and patients toward the most effective course of therapy areother advantages. The benefits of medical IoT are numerous, as outlined in [13 - 15].

These benefits include but are not limited to the following points:

- **Remote Patient Monitoring:** With various sensors that can run specific tests on the patient's body, medical personnel can remotely monitor patients. The elderly and others with chronic illnesses can benefit from this.
- **Cost Reduction:** Given remote patient monitoring, it is probable that the number of doctor visits and hospital stays will decline and the overall cost of medication will reduce.

CHAPTER 6

A Neural Network Approach for Early Detection of Parkinson's Disease from Speech Data Using Linear and Nonlinear Dynamic Features

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Abstract: Parkinson's disease is a progressive neurological disorder brought on by the depletion of the substantia nigra's dopamine-containing cells, which plays an important role in movement. Bradykinesia (slowness of movement), akinesia (impairment of voluntary movement), tremor, and speech impairment are other symptoms. Typically, 80% of the striatal dopamine has been depleted and 60% of the nigrostriatal neurons would have died by the time the condition is recognised. Speech issues are seen in 89% of patients with PD. The voice of the affected individual alters; they either talk quietly or struggle to make words. A husky voice results from the afflicted face, mouth, throat, and neck muscles. They have trouble communicating. Lowered intensity, suppressed pitch, slight accurate utterance, stumbling, maundering, vocal tremors, monotony in conversation, harsh voice, sternness and stiffness in the laryngeal and ribcage muscles, and fast bursts are characteristics of the speech disorder. Currently, the doctor's domain expertise is used to identify the disease condition. Numerous assessments are made, and further therapies are advised. There is a need to discover the pattern when data is increasing at a rapid rate so that the patterns may be automatically recognized by a non-invasive technology and the condition can be simply and affordably diagnosed. The voices of those who have Parkinson's disease and who are age and gender-matched were compared in this study using dynamic voice features, including jitter, shimmer, RPDE, PPE and DFA. We propose a method that makes use of neural network approach to determine whether a person is healthy or Parkinson's disease patient. The accuracy value for the suggested method was found to be 98%. We also evaluate the proposed model using the SVR technique with hyperparameter optimization to calculate the Mean error and determine the degree of correlation of the features selected for the proposed work.

Keywords: Hyperparameter optimization, Neural network, Parkinson's disease, Speech features, Support vector regression.

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INTRODUCTION

The motor system and basal ganglia are both affected by Parkinson's disease (PD), a neurological condition, which is responsible for choosing, coordinating, and executing the movement. The diaphragm and laryngeal muscles that are used for speaking and singing are impacted. Although 5-10% of cases have an early beginning, this condition is more prevalent among elderly persons. Globally, 6.8 million individuals are impacted by it.

Parkinson's disease damages brain function by destroying brain cells [1]. Parkinson's disease can be identified after considerable harm has already been done to critical brain cells. Prior to the period when changes in brain cells occur, the voice alters sooner. Up to 60% of the brain's neurons responsible for controlling movement are protected from damage by early diagnosis, which also leads to better and more efficient therapy.

People with Parkinson's disease frequently experience voice and speech issues [2]. Over seven million Parkinson's disease patients worldwide may have speech problems between 75 and 90 percent of the time. Patients with Parkinson's disease frequently have a monotonous, low-volume voice. The speech style is frequently brief bursts with pauses in between sentences and lengthy pauses before speaking. Slurred speech is another possibility.

Parkinson's disease seldom affects individuals under the age of 50, although for a tiny percentage of patients, the condition does. Parkinson's disease affects people on average when they are 60 years old and its likelihood of occurrence rises with ageing. Young-onset Parkinson's is a term used to describe conditions that start earlier than that. Men are somewhat more likely than women to experience it. The epidemiology and clinical characteristics of the illness clearly differ between the genders; males are affected by PD twice as frequently as women. This is brought on by the elevated estrogen levels in females. The dopaminergic neurons are known to be protected by estrogens from any unfavourable circumstances. The death rate and disease progression are both greater in men [3, 4]. According to epidemiological research, males have a 1.5–2 times greater probability of PD than women. In addition, women's onset was somewhat later than men's in 6 out of 8 incidence studies that mentioned gender-specific age at onset.

Medical diagnosis is a classification problem. To determine if a patient has a disease condition or not and, to classify them into different degrees of a disease, signs and symptoms must be assessed. The application of neural networks has the potential to help doctors diagnose patients more accurately or perhaps discover new patterns that can help with diagnosis.

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According to research, speech production may be modelled as a nonlinear dynamical system in which little changes in the way its components interact to lead to chaotic yet predictable behaviour. The dynamics of the entire system can be impacted by vocal organs, muscle, and nerve deficits associated with Parkinson's disease, indicating that nonlinear methods may be useful for predicting the stage of the condition using voice recordings.

LITERATURE REVIEW

Many authors have conducted numerous researches to study PD patients' speech with the goal of identifying PD and determining the severity of the condition. Before the nerve cells are impacted, PD sufferers' voices can alter and be recognised. Reviewing papers on voice has given us important knowledge about Parkinson's condition. The work of M. A. Little is among the most well-reviewed contributions that went into building the database with 22 voice characteristics [5 - 7]. In a study [8], techniques such as multilayer perceptron, sequential minimal optimization, J48 which is based on Iterative Dichotomiser, were used to calculate the sensitivity, specificity, and accuracy for voice characteristics. The values of 97.8, 100%, and 95.75% for MLP's accuracy, specificity, and sensitivity were the highest. The following metrics were computed [9]: accuracy, sensitivity, specificity, projected value in both the positive and negative. Positive predictive value for MLP was high at 95.83%, while sensitivity for SVM with a linear kernel was the greatest at 99.32% and Negative predictive value was the highest at 97.06%. SVM using kernel puk obtained a classification accuracy of 93.33% and positive predictive value of 96.53%.

According to a study [10], all the classifiers showed a solid level of performance, the best results were obtained with boosted logistic regression, which had a 97.16% accuracy rate and a 98.9% ROC area. It was also noted that virtually all of the classifiers utilized had similar accuracy and ROC curve areas. A review of relevant studies was also performed [11].

As in some studies [12 - 14], a large number of researchers worked on various audio data sets to increase detection accuracy through feature engineering or the use of various classifiers for constructing telemonitoring systems. To lessen dimensionality, they also researched several feature selection methods. None of them, however, are known to look at age and gender-based models. Given that Parkinson's condition is more common in males, and that male and female speech qualities differ significantly, it is unclear if a gender-based detection technique will improve accuracy.

The majority of traditional diagnoses employed motor skill assessments to predict PD. The existing approaches for detecting PD symptoms, however, are only

Detecting COVID From CT Images using Autoencoders

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Abstract: The SARS-CoV-2 virus, popularly referred to as Coronavirus or COVID-19, spread widely and infected a huge number of people since December 2019. There are various tests now detecting Covid 19, however, each of these tests has its own disadvantages. CT (Computed Tomography) scans are one of the most efficient ways of diagnosing covid 19 among these tests. The effectiveness of CT scans is much greater than that of X-rays. However, these scans cannot yield results directly by just looking at them, because there are other common infections such as pneumonia and influenza, which yield similar lung images under infection. Hence it is imperative for us to use ML and DL for fine classification and better results. The primary algorithm used for classification is the convolution neural network, which gave outstanding results, but the complexity of the program was drastically increased. Many deep learning approaches produced good results but one of the major limitations is that only a limited dataset was used for training purposes. The dataset gathered to date is still found to be small as it is a matter of privacy concern. In this paper, autoencoders were used for the data augmentation process so that we extract only the important features from the images. A 2+2 layer autoencoder was used to find out the last layer used for image augmentation. This was followed by designing and developing 3 autoencoders, which yielded a satisfactory result. Finally, the images were fed into various models designed to classify if the image belonged to the COVID class or not. To avoid overfitting, only 2 CNN followed by a flattening layer followed by two dense layers. Another step is taken to avoid overfitting by using regularizes like dropout and kernel regularizations. For the testing accuracy, we converted the 256,256,1 images to 64,64,192 using the three encoders we trained. The model gives an average accuracy of 83.33%, precision of 77.77%, recall of 90.0%, and F1-score rate of 83.44%. Based on our results, we conclude that our model can differentiate COVID-19 images, which might aid radiologists when evaluating suspected COVID-19 cases.

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Keywords: Autoencoder, Accuracy, CNN, F-measure, Max pooling, Precision, Recall.

INTRODUCTION

In December 2019, SARS (Severe Acute Respiratory Syndrome) is caused by CoV-2, the Coronavirus. All coronavirus-infected patients developed mild to severe COVID-19 respiratory illness symptoms. The illness spreads over the world rapidly in the months that follow. The COVID-19 virus was classified as a global pandemic by the World Health Organization on March 11, 2020. One of the causes of the disease's rapid spread is the inefficiency of global detection. Both the COVID-19 nucleic acid sequencing method and the nucleic acid detection kit method (TR-PCR) can be used to detect the virus of the COVID-19 virus's isolation and genome sequencing. The TR-PCR test, on the other hand, requires at least 4 hours of time for the results to be obtained. The nucleic acid sequencing process, on the other hand, takes substantially longer. This virus is transmitted *via* respiratory organs, resulting in fast virus transmission. It causes little illness in the majority of patients, and some persons have a serious infection. There will be a lack of reagents and equipment for these diagnostic tests in certain countries and regions with low budgets, resulting in delays in early detection, which led to the rapid spread of the virus(COVID-19) around the world.

We focused on the global issue of coronavirus illness identification using chest radiography pictures in this work. Early investments in defining this viral infection can significantly improve the epidemic response in terms of swift and ongoing surveillance and subject evaluation. To determine the presence and degree of COVID-19, the patient is scanned using Computer Tomography (CT), X-ray, and Ultrasound (US) methods. The first step in treating coronavirus is screening patients in small medical clinics or hospitals. Medical imaging is now used in hospitals for patients with severe respiratory symptoms because it is simple and quick, enabling doctors to recognize diseases and their effects more quickly. Transcription-Polymerase Chain Reaction (PCR) tests are still used for final diagnosis.

Patients must be screened in medical facilities or primary care offices in order to receive an initial diagnosis of COVID-19. Medical imaging is now used in hospitals for patients with severe respiratory symptoms because it is quick and simple to use, allowing doctors to quickly identify diseases and their effects. PCR (transcription polymerase chain reaction) tests are still used for final diagnosis. This problem can be resolved using deep learning techniques. It has advanced significantly in recent years as a result of rising computer power, an increase in data, and ongoing deep learning model and algorithm improvements, as shown by

record-breaking performance in challenge competitions. The goal of deep learning is to create a multi-layered machine learning model that has been trained with a lot of sample data to increase the precision of classification and prediction [1, 2].

It is just as vital to estimate infected people's chances of survival as it is to discover the virus early.

When resources are few, medical centers can consider patients' needs and make the most use of what they have. Deep neural networks proved to be effective in the early identification of COVID-1 in a previous study on COVID-19 detection [3]. Reconstruction techniques using autoencoders on computed tomography images have been performed for COVID-19 detections. U-Net-based architectures [4] have been used to partition many infected regions in the chest CT images. There are various studies that exhibited the use of auto encoders for covid detection.

The success of deep learning especially for image detection is comparatively higher than any other methods. The autoencoders combined with convolutional neural networks have remarkably given good results when compared to other methods. A lot of research is being done on the SARS virus as the virus keeps mutating day by day, and it poses a serious concern to doctors and people. Hence, it is imperative to diagnose the issue as soon as possible, so that treatments can be started accordingly. Early diagnosis helps to save lives faster. There is a lot of research involving this concept, but a major problem is either the model was trained using a small set of data or the model involves large time and space complexity.

In this paper, we will focus on the following things. To yield better results in terms of space complexity and time complexity with minimum autoencoders in the section. We used a convolutional autoencoder for data augmentation and feature extraction. Once the necessary features have been extracted, the data is fed into the convolutional neural networks where after processing, it will state whether the image fed is covid-positive or covid-negative.

LITERATURE SURVEY

This section contains the literature survey taken for this paper. One of the early learning models was given by some authors [5] where they used a modified inception transfer-learning model. This model used 1065 CT images, of which 325 images correspond to coronavirus images and 740 images correspond to viral pneumonia. The model had an accuracy of 79.3% and a specificity of 0.83. Another model given [6] was a 2D deep convolutional neural network that had

Improvement in Public Health through Technology

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Abstract: "Public health" is the science and art of preventing disease, extending life, and promoting health through community efforts. Cutting-edge treatment approaches, enhanced diagnostic tools, mobile healthcare apps, telemedicine, digital transformations, and similar innovations have ushered in an abundance of opportunities for assuring the success of public health programmes. Many such instances can explain how technology can significantly enhance public health. One such instance is called "mHealth", which assigns five key roles to the wearables: sensing, analysing, storing, sharing, and applying data for the use of mobile devices, such as smartphones, tablets, and PCs, for the improvement of public health by taking care of an individual.

Keywords: Community effort, Public health, Social media, WHO.

INTRODUCTION

The World Health Organization (WHO) defines health as "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity." As a result of this expansive and aspirational definition, people began focusing not only on the physical aspect of health but also on its emotional and social aspects. In other words, people began to consider health in a more holistic manner. As a result, a new discipline within the fields of science and art has emerged, known as "public health". Therefore, public health is defined as "the science and art of preventing disease, extending life, and promoting health through coordinated community efforts." Due to the combined efforts of these parties, public health evolved in a manner distinct from conventional clinical

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treatment [1 - 4]. In the case of general clinical therapy, the doctor focuses on the current problem that the patient is experiencing, which includes both the illness and the recovery process. The method known as "public health", on the other hand, takes an entirely different, more holistic approach. It investigates the "whys" and "hows" of a person contracting a disease in an effort to comprehend why and how it occurred. Was there a problem with his living conditions, such as a lack of access to clean water or nutritious food? Was this individual under the influence of bad behaviours, such as alcoholism, drug use, *etc.*, or did they lack knowledge about health and hygiene? Are there any laws or resources that might be used to either enforce specific health and hygiene standards or avoid the occurrence of certain scenarios? What are the community's expectations of this person, and how do they feel about their illnesses? Does the client have access to a robust social support network that can aid in the individual's early recovery or assist them in avoiding repeat occurrences? Can this individual afford either the cost of treatment or keeping a healthy lifestyle? What are the reasons if not? Does the individual have a job that satisfies their requirements and pays well? What are the reasons if not? Is it feasible that the individual in issue lacked enough educational opportunities? etc. Therefore, public health considers the situation of an individual's health as a complicated interplay between several elements. In addition to the individual's features and lifestyle, these variables also encompass the individual's physical, social, and economic surroundings. In this way, "public health" has had a significant impact on the health of the population, as opposed to the health of individuals, by keeping people healthy and saving lives [1, 5].

The ground-breaking discoveries and developments now occurring in the healthcare business have a positive impact on public health. The ultimate objective of almost all prospective developments and discoveries is to enhance "public health" in as many diverse ways as possible. For example, cutting-edge treatment approaches, enhanced diagnostic tools, remote consultation, mobile healthcare apps, telemedicine, digital transformations, and similar innovations have ushered in an abundance of new opportunities for assuring the success of public health programmes. The technologies used in public health provide medical workers access to increasingly advanced instruments, enabling them to get accurate data in real time. Later on, the acquired information supports medical professionals in establishing more effective and implementable health plans to handle a range of difficulties, starting with data-gathering tools and advancing to life-saving equipment and treatment approaches [6 - 10].

As a consequence, there have been several significant advancements in public health, much too numerous to cover here. Moreover, with advancement comes challenges. As a consequence, this article not only discusses the latest advancements but also outlines a number of roadblocks to improved public health

Public Health through Technology

intervention practises. Backlogs that may emerge as a result of funding shortages, the accelerating rate of climate change, the present global pandemic or other similar impending threats, public trust in government and leadership, *etc.*, are all examples of the kind of serious problems that may arise. In this chapter, we provide a hopeful outlook on future advancements and the challenges facing public health.

SPECULATING ON THE FUTURE

A community-driven, multi-sector health ecosystem is essential to attaining the basic human right to health and prosperity. The primary role of public health as a protector of population health will guarantee that it stays at the helm of all systems — education, transportation, technology, communication, etc. — that influence a country's overall health. Leaders in public health will serve as their communities' primary health strategy decision-makers, creating collaborations across sectors and using cutting-edge technologies to establish priorities for enhancing the public's well-being, therefore attracting the attention of prospective funders. Recent technological advancements have greatly improved public health, and health technology is an exciting and fast-increasing subject. Antibiotics, penicillin, X-rays, and radiography are just a few of the many scientific discoveries and advancements that have paved the way for modern medicine and continue to do so to this day, expanding healthcare options. According to a study conducted by the World Health Organization (WHO), digital technologies have "generated new patterns of communication, empowerment, and involvement" and "opened up a plethora of opportunities for shaping the future of primary health care and ensuring effective public health action." As a result of advancements in fields such as 3D printing, nanotechnology, robotics, artificial intelligence, and virtual reality, the public health field can now explore new avenues. Listed below are many instances of how technology may significantly enhance public health:

Geospatial Engineering

One of the most interesting applications of geospatial technology in the field of healthcare may be its ability to provide information that may help in the improvement of public health. Geospatial technology gathers data on several parameters, analyses the obtained data, and shows the findings on a multi-layered map. For instance, geospatial technology may give detailed information on the occurrence of diseases in a particular location, health risks depending on age demographics, care delivery logistics, and other social elements that impact the overall health of a community. These multi-layered maps have the ability to provide both experts and the general public with accurate information on the state

Statistical Approach-Based Medical Data Analytics

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Abstract: Analysis is a meaningful procedure in which the medical field is mostly preferred for finding innovations. There are many observations and implementations based on various tools for statistical results. Successful experimentation, which demands improved medical interventions, is one of the approaches undertaken using SPSS, R programming, and enterprise software. Some of the diseases considered for medical observations are cancer, influenza, and communicable and non-communicable diseases. This research work mainly contributes to its importance in finding statistical results based on non-communicable diseases. One of the non-communicable diseases commonly known as meningitis is discussed in this work to showcase the various comparisons of statistical approaches. From the World Mortality Database (WMD), the disease dataset is handled for monitoring the membranes and their range of fluids that are average or vary based on severity. Comparing the variations to find the symptoms can increase the efficiency of treatment. Some of the appropriate methods that can suit this non-communicable flu are categorized in this research work using the Improved Medical Circumferential Factor Approach (IMCFA). Simultaneous work has been carried out to undergo this state based on exploratory data analysis, multivariate steps, and graphical representations. Based on a comparison of the IMCFA, univariate, multivariate, and graphical methods of meningitis, accurate predictors of the disease were found.

Keywords: Communicable flu, Exploratory data analysis, Improved medical circumferential factor approach, Meningitis, Univariate, World mortality database.

INTRODUCTION

The development and growth of industries mostly evolved from a statistical approach only. The efficient results based on the analysis are built in many fields to understand the level of involvement. Research ideas and medical problems are common terms that improve the quality of work or ideas. The purpose of the

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database is to enhance the necessity of medicines, lab experiments, and much more. There are many steps involved in statistical medical analysis, which are measured in various measures to handle massive data collected from medical fields [7].

Programming and coding are powerful steps that can travel through multiple methods that can compute the parameters. Backgrounds based on medical reasons are too complicated since the growth of data is increasing in more numbers. Thus, the results and their outcomes rely on probabilistic ranges that can improve the centric and its experiences, which can develop more solutions. Machine learning is a domain where analysis is one of the major steps that can be handled for various applications [8]. One of the major limitations of machine learning is inconsistency in the data. As there are basic pipelines that can analyze the rate of the development process, the initial step is to collect the data and then prepare the processed data. Based on the model, there are various steps such as hypertuning the features and then training according to the consistency. About 70% of data are trained, and 30% of data are tested, which uses the model for better results [9]. By using the ML techniques, various steps were incorporated to find useful text details. In the medical field, there are many separate data that need to be taken care of for various steps. A number of results were implemented using classification algorithms for lung cancer, brain disorders, and so on. This research work discussed a non-communicable disease named Meningitis, which is highlighted here for statistical approaches. Meningitis and its involvement using machine learning are highlighted in this work [10]. This is a type of inflammation that occurs due to some fluid and also membranes that cover the brain portion along with the spinal cord.

Machine Learning

Human intelligence is associated with the ability to perform tasks by a computer in the case of domains such as artificial intelligence. The major function of AI is to deal with the data present in huge quantities and healthcare is one such field where enormous data is being generated on an hourly basis. Such domains are a necessity of classification algorithms in machine learning. Recognition of patterns is performed with the help of ML methods. Diagnosis of a disease can be done with AI techniques along with therapy thereby handling the management of human health [11]. The patterns present in the chosen dataset are identified and based on that, analysis is performed in the case of machine learning. The score of risk is computed for making predictions as well as decisions for treatment [12]. The accuracy parameter also varies while considering the patients individually. Medical Data Analytics

Meningitis

Among the challenges in the domain of healthcare, meningitis remains a challenging disease and needs to be given the utmost care. The meninges get inflamed along with the spinal cord and the blood cell count reaches an abnormal count in meningitis [13]. This disease may be caused by a virus and also bacteria. Meningitis caused by viruses needs to be diagnosed by automated methods due to the absence of successful antibiotic remedies. Meningitis resulting from bacterial infection can be identified based on symptoms such as pain in the head, light sensitivity and stiffness in the neck. Patients affected by HIV are easily affected by meningitis. Fig. (1) represents agents causing meningitis.



Fig. (1). Agents causing Meningitis.

Types of Statistical Approaches

Fig. (2) shows medical data analysis using statistics representing the various approaches that are involved in outcome-based research. The initial idea displays the feature description that can have various methodologies for understanding medical features and increasing the credit range. The second approach is the occurrence approach which depends on the probability of solutions that can display the range of improved outputs [14]. The third approach is predictive analysis which can handle a series of data that can describe the variation in many fields such as weather telecasting climatic changes, reports of various markets, *etc.*

The fourth approach is exploratory data analysis which can have both uni and multi-feature analysis [15]. The final approach for a statistical process is the decision-finding approach, which is mostly used in marketing and business

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