The Role of AI in Predicting and Managing Chronic Diseases

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ABSTRACT

Chronic illness, such as renal or heart disease, is now ranked among the main causes of mortality globally. Preventing chronic illness is a very difficult endeavour. Only chronic sickness may be predicted by medical professionals who have experience and knowledge with this illness. The Internet of Things (IoT) is a critical piece of technology in a healthcare system. This research proposes the EO-LWAMCNet model, an EO optimized Lighter Automatic modulator classification network, to reliably predict a patient's chronic health status (heart or kidney illness). The term "edge AI" refers to artificial intelligence (AI) and data analytics that use federated learning, deep learning, and deep learning models that are implemented and run at the network's edge, away from centralized data centres. Artificial Intelligence (AI) facilitates the meticulous examination of extensive datasets that come from many sources, including as wearable technology, demographic data, and digital health records. This allows for the identification of complex trends and predictions of an individual's future health. This forecast is further strengthened by federated learning, a breakthrough method in AI allowing cooperative training of artificial intelligence (AI) algorithms on dispersed edge computing devices while retaining privacy. By processing and analysing data locally, edge computing lowers latency and facilitates quick choices. In the event of an aberrant outcome, the doctor receives an awareness message to treat the patient. The model's efficiency is assessed using the following metrics: accuracy, miss rate, MCC, and F1-score. Using the CKD dataset, this model has an accuracy of 93.5%, and when using the HD dataset, it has an accuracy of 94% in predicting whether there is or absence of heart or kidney disease. Furthermore, the model's classification miss rate is lower.

Keywords: Internet of Things (IoT), kidney disease, Artificial Intelligence (AI), CKD dataset, accuracy, AI models, health condition, Edge AI, healthcare system.

INTRODUCTION

The sheer number of data produced by individuals and gadgets has increased exponentially as a result of digital technology. This has given rise to fresh ideas in the field of wellness about the prompt identification and treatment of illnesses, enhancing patient outcomes, and cutting costs overall [1]. One of the fastest growing fields for development is the use of AI and computing close to healthcare, which has the potential to completely transform how medical professionals track and anticipate disease outbreaks [2].

The healthcare industry has made significant advancements in recent times. By integrating Internet of Things (IoT) devices, real-time bodily surveillance and remote healthcare monitoring have been made possible.

Furthermore, it serves as a crucial acquisition element for the vast applications that promote interaction between people and objects. The handling, storage, and management of the vast amounts of data produced by the devices is the main issue facing the IoT-based medical field [3, 4]. By enabling data to be held anywhere and accessible whenever needed, cloud computing resolves these problems and significantly lowers storage costs.

Using these IoT and cloud approaches in the medical sector expanded the possibilities for managing modern scenarios with more sophisticated services in a decentralized and scalable manner. Artificial intelligence aids in the analysis, [5], detection, and diagnosis of illnesses. In addition, artificial intelligence correctly categorize illnesses. As a result, several AI algorithms are developed to promptly and reliably predict illnesses at an earlier stage [6].

The development of Machine Learning (ML) techniques has enhanced the healthcare industry by streamlining the method of identifying illnesses [7]. It is particularly beneficial for those who live in remote and rural places. Heartbeats and blood pressure readings are used to track and monitor physical wellness. Reliable medical diagnosis is often achieved with using of machine learning and deep learning methods. They are able to divide up illnesses and forecast defects. Deep learning models solve problems that machine learning algorithms cannot, such as the inadequacy with their huge data processing capabilities [7, 8]. Deep learning techniques include more hidden layers and were trained on the original, vast amounts of data, increasing prediction accuracy. To improve prediction accuracy, more data types, both structured and unstructured, methods have been introduced.

Particularly AI disease detection methods focus just on illness prediction, ignoring concerns about data security and privacy, [9, 10], which are particularly important when storing private material like medical data. Additionally, additional techniques meant more time was needed to master features, which meant additional classroom time.

Smartphones, a variety of sensors, and computerized medical records are just a few of the sources of healthcare data. These data may be analysed by AI algorithms to find trends and patterns that could point to the beginning of a diseased [11]. AI may be used to create focused treatments to stop disease outbreaks and generate accurate forecasts about foreseeable medical outcomes by merging this data with additional relevant information such as demographic and external factors [11, 12].

On the other hand, the rapidly developing field of edge computing aims to address the challenges involved in processing and sending enormous volumes of data as they are produced. Edge computing brings processing power closer to the data source, which may greatly decrease latency and speed up processing [12, 13]. It is the best option for systems that need to analyse data and make decisions in real time.

Edge computing is very helpful in the healthcare industry for operations that need to make decisions and monitor patients in real time, including wearable technology for monitoring of patients and remote medical diagnosis and treatment [13, 14]. Healthcare providers may develop creative solutions that enhance patient satisfaction, reduce expenses related to healthcare, and contribute to better public health outcomes by fusing the advantages of edge computing with artificial intelligence.

The Centres for Disease Control and Prevention state that treating patients with ongoing medical conditions makes up 86% of health care costs and causes seven out of ten deaths annually. Chronic diseases include illnesses such as diabetes, asthma, heart disease, pneumonia, lung cancer, depression, stroke, the condition, and Alzheimer's.

More than fourteen million Americans suffer from a chronic medical condition, and at least 10 million more cases are predicted to be added to the population every ten years. Chronic care expenses have increased over the last several decades in tandem with the country's expanding patient base, and they now make up more than 75% of all national health spending in the US. Sixty-eight percent of Medicare enrolees have two or more ongoing medical conditions [14, 15].

"An integrated care method for manage illness which includes assessments check-ups, surveillance and coordination of medication, and patient education" is what the term chronic disease administration refers to. In order to accomplish the "triple aim" of healthcare—improving patient health and outcomes as well as their quality of life; expanding access to healthcare facilities; and lowering healthcare costs by preventing or lessening the effects of a disease—addressing chronic diseases necessitates new approaches, instruments, and care processes.

These technical developments in instruments and techniques have enormous potential for coming up with innovative answers to these problems. For instance, telehealth programs may help people with chronic diseases with their physical and emotional needs.

This article examines Edge AI's function in early disease forecasting and outlines its advantages, limitations, and practical uses in the medical profession. It talks about the difficulties that need to be solved and the condition of the sector right now. It also looks into how Edge AI could advance public health in the future. Establishing a thorough grasp of Edge AI's applications and ramifications is crucial given its growing relevance in the field of healthcare. A number of previous review articles have examined aspects of artificial intelligence (AI) in the medical field, primarily concentrating on particular illnesses, imaging modalities, or AI methodologies. We explain how, by adopting a wider and more inclusive viewpoint, our study differs from these review papers.

The study also examines the latest uses of FML in a range of illness prediction tasks, including the prediction of diabetes, cancer, and cardiovascular disease. Perform a thorough literature analysis of the most recent wearables that are capable of detecting and tracking Cardiovascular Disorders (CVDs), the world's leading cause of death, in a different project. They concentrate on the varieties, characteristics, and uses of wearable technology, including smartwatches, bands, rings, and eyeglasses that may monitor different physiological signals, including signals from the electrocardiogram, also known as the ECG, Photoplethysmogram (PPG), Blood Pressure may (BP), and the Heart Rate (HR). A new technology called the Internet of Things (IoT) is utilized for making everything smart. The medical industry is seen to be the most appealing among of the many industries that the Internet of Things has a significant influence on. Through remote monitoring systems, IoT has the ability to automatically link sensors, equipment, and patients without the need for human interaction. An IoT subdomain is a Wireless Bodily Area Network (WBAN). It's a wireless sensor system that allows for remote monitoring of a patient's vital signs by connecting wearable devices, or gauges, to the network on the patient's body. Within the field of medicine, a WBAN is comprised of a compact network of sensors, including gyroscopes, spirometers, pulse oximeters, GPS units, and Electrooculography (ECO).

Objectives of the Study

- Assess the status of artificial intelligence (AI) technologies today, such as predictive modelling and machine learning algorithms, in the diagnosis and treatment of chronic illnesses.

- Examine how AI helps create individualized treatment programs and treatments based on the information and features of each unique patient.
- Analyse how well AI-driven interventions work to encourage positive lifestyle choices and healthy habits.

LITERATURE REVIEW

(Ati, M., 2019) [16] One of the leading causes of mortality globally is chronic illness, which adds significantly to the burden of disease worldwide. These illnesses are serious and enduring. They have a long-lasting impact on people, melding and influencing their quality of life. To accurately forecast diagnoses and assist patients in managing their diseases, it is crucial to establish the proper processes in the right locations. The goal of this project is to develop an electronic health records management system that can anticipate chronic illness diagnoses. By identifying chronic illnesses early on and keeping track of patients' health as they get the necessary therapies, the system facilitates diagnosis and lessens the severity of these conditions. To create the system, six distinct classification algorithms were tested and assessed using performance metrics including preciseness, precision, and recollection for the prediction of chronic diseases.

(Bardhan, I., Chen, H., 2018) [17] According to the Centres for the Control of Disease and Prevention, treating patients with long-term illnesses accounts for 86% of health care costs. Chronic diseases include diabetes, asthma, coronary heart disease, lung disease, malignancies, depressive disorders, stroke, elevated blood pressure, and Alzheimer's. These conditions cause seven out of ten deaths annually. In all, over 140 million American struggle with one or more chronic illnesses, and at least 10 million more cases are predicted to be added to the population every ten years. Chronic care expenses have increased over the last several decades in tandem with the country's expanding patient base, and they now make up more than 75% of all national health spending in the US. Sixty-eight percent of Medicaid enrolees have two or more chronic illnesses.

(Egon, K., 2017) [18] It is possible that the abstract for "machines" Learning and Chronic Wellness Management: Adapting Care for Superior Outcomes" addresses machine learning applications in relation to managing chronic diseases. It may draw attention to the value of individualized treatment, the function of various machine learning algorithms, and the possible advantages of applying AI to the medical field. It could also discuss the difficulties, moral dilemmas, and upcoming developments in machine learning for the treatment of chronic illnesses.

(Agarwal, S., 2019) [19] Predicting chronic illness mortality early on allows for proactive measures to be taken to avoid the condition. This is the only option to combat that problem. In a situation like this, machine learning in general is highly recommended for the patient's needs. The major goal is to compile every paper that has ever been published on illness prediction and draw conclusions about the scope of the research that has been accomplished. In order to perform this study, we reviewed the literature on several machine learning algorithms that are used to efficiently forecast illnesses, with an emphasis on research published from 2017 to the present. People may be diagnosed based on their symptoms thanks to features, independent variable selection, and the integration of various algorithms, which have been shown to improve a disease prediction system's accuracy and performance.

(Wang, B., 2018) [20] Artificial intelligence (AI) for medical applications is becoming more and more important due to the growing need for resources, particularly in the treatment of chronic diseases. The viewpoints of chronic customers, who are among the key users and risk-takers of these technologies, are still mostly unexplored even as AI-based home healthcare systems are being created. Even while recent studies have emphasized the significance of AI-based residential care systems, little is currently known about the features and designs that patients would like. The viewpoints of chronic patients on AI-based homecare systems are examined in this work, which fills a research gap in this field. We seek to understand the variables influencing their choice to employ these systems, clarify the possible responsibilities of the government and other relevant authorities, and offer input to the makers of artificial intelligence in order to improve system design, adoption, and usability as well as the overall healthcare experiences of patients with chronic conditions. (Barrett, M., 2019) [21] One of the most complicated chronic conditions, Heart Failure (HF) is quite common and is mostly brought on by aging populations and improved management of underlying illnesses. The prevalence will keep rising. It is the leading cause of hospital for patients 65 years of age or older, that has major financial and societal ramifications. Not all patients benefit equally from the current "one-size-fits-all" strategy to treating HF. The effective care of patients with HF is quickly jeopardized by these factors. An unconventional strategy based on a fresh understanding of care is needed. We suggest a brand-new approach to personalized, preventative, and predictive medicine in which patients really take charge of their care. This approach is backed by an intuitive mobile application that leverages artificial intelligence.

(Hussein, A. S., 2012) [22] By offering reliable and accurate illness risk diagnostic prediction and medical guidance recommendations, healthcare system recommendations for chronic diseases diagnostic (also known as CDD) may significantly contribute to disease control. This helps people have 24-hour access to health services and helps healthcare practitioners maintain a system for remote monitoring of patients around-the-clock. These systems are thought of as additional resources to help doctors and patients manage and control the illness. It is difficult to provide an accurate real-time idea for medical data given the complexity of the data, which is often represented by huge, noisy, multidimensional, imbalanced, and/or missing data. The goal of the CDD system is to provide highly accurate recommendations for medical guidance and illness risk prediction. This research proposes a hybrid strategy based on various classifications and united cooperative filtering to develop a CDD recommendation system.

(Minghui, Y., 2017) [23] Unquestionably, AI is transforming patient care and medical research in a variety of domains. An essential aspect of medical management, prolonged nursing care, has greatly benefited from Intelligence in a number of ways. In advance of implementing AI, it is essential to understand its working principals in order to prevent AI from being used to replace duties arbitrarily. Nurses are the main players in symptom group research, which goes beyond diabetes to include other chronic illnesses. They are primarily in charge of documenting patients' regular symptoms and vital signs. But a significant amount of recent AI research leaves nurses out of the development stage, including them only in user and evaluation groups.

METHOD

Normally, the patient's body is covered with the IoT sensor to gather vital signs. These indications are subsequently put into the medical app. The PHR, or patient health records, include a vast amount of data in many formats [24]. The Disease Prediction Systems (DPS) is used by the hospital to keep a close watch on the detected data values. The recommended approach forecasts the patient's illness using a LWADCNet. The system has been verified and trained for this purpose. The suggested model uses the CKD and HD statistics as input.

Gathering data

Each row displays a different patient's medical record. The medical records of the person include blood pressure levels, hypertension, albumin, serum, type 2 diabetes, number of years smoked, history of diabetes, [25], sleeping electrocardiogram readings, and other data that are identified as elements of the dataset.

Pre-processing the data

Three procedures comprise the pre-processing: normalization, term waste removal, and replacement of missing data. The lacking characteristics are swapped using the maximum total of repeated value pairs for features. Values that are similar in the majority of a patient's attributes are swapped by the same position.

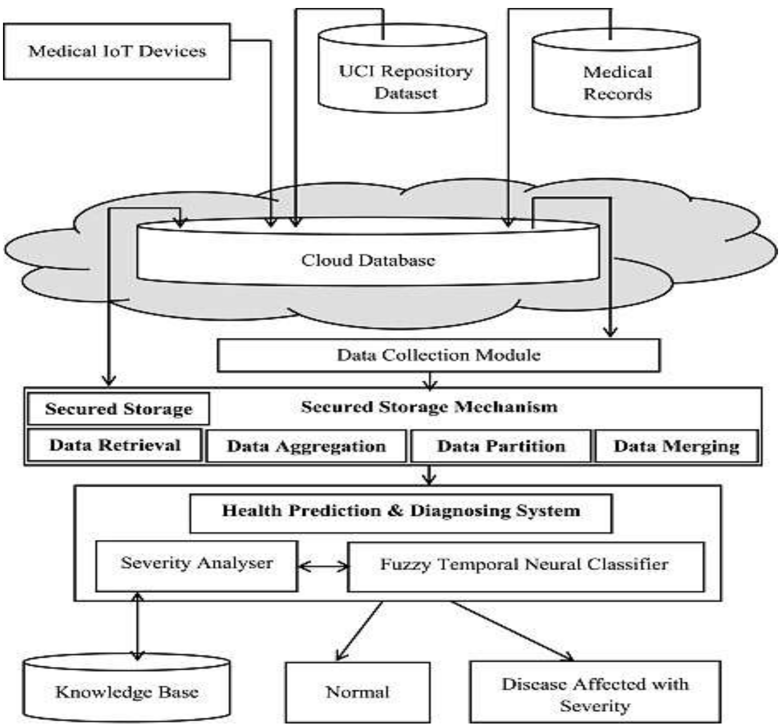

Fig. 1 Predicting Chronic Illnesses in Cloud Architecture Based on IoT.

$$\widetilde{H_n} = \sigma\, ReLU\left(\sum_{j,i,}\tilde{J}_{j,i,n}.\,\widetilde{\widetilde{E_{j,i,n}} + \widetilde{a_n}}\right) \text{............1}$$

$$\overline{G_0} = \overrightarrow{Generation_{rate}} * (\overrightarrow{d_{eq}} - \vec{\sigma} * D) \text{...........2}$$

$$\overrightarrow{Genration_{\,rate}} = \{\begin{matrix} 0.5\ R_1\ R_2 > p \\ 0\ otherwise \end{matrix}, \text{.......3}$$

$$\vec{D} = \overrightarrow{d_{eq}} + (\vec{D} - \overrightarrow{d_{eq}} * \vec{B} + \frac{\vec{G}}{\overrightarrow{\sigma * C}} * (1 - \vec{B}) \text{.......4}$$

RESULTS AND DISCUSSION

The 11th generation Intel Core i5-1135G7 machine running Windows 11 is used for the tests. The MATLAB library is used to carry out the simulation activities. To test the approaches, the two-disease diagnosis CKD and HD dataset are selected. The suggested technique is compared with the three modern approaches of MSSO-ANFIS, T-RNN, and DLMNN to determine the ratios of prediction efficiencies in regard to the accuracy measurement, F1-score, and MCC. Our mini-batch size is set to 64, the initial rate of learning is set to 0.001, the value of the weight degradation is set to 0.00001, [26], and The Amstrad is set to true in the LWAMCNet's initial parameters.

Metrics for performance assessment

The primary purpose of this section is to provide the many performance assessment measures that are used to assess the effectiveness of various classifiers. Accuracy is the proportion of classes that are properly recognized out of all the occurrences in the dataset.

$$Accuracy = \frac{Tpos+Tneg}{Tpos+Tneg+Fpois+Fneg} \ldots\ldots\ldots 5$$

$$Precision = \frac{Tpos}{Tpos+Fpos} \ldots\ldots\ldots\ldots 6$$

$$Recall = \frac{Tpos}{Tpos+Fneg} \ldots\ldots\ldots 7$$

$$F1-score = \frac{2*Tpos}{2*Tpos*Fpos+Fneg} \ldots\ldots 8$$

The prevalence of misclassification is primarily used to calculate the percentage of inaccurate predictions the model made. The used measure does not distinguish between the framework's positive and negative predictions [27]. Table 1 compares the miss identification rate of the hypothesized EO-LWADCNet methodology with those of other techniques already in use, including DLMNN, MSSOANFIS, and T-RNN.

Table 1 Miss Rate comparison of the suggested EO-LWAMCNet using current methods.

Technique	Proposed EO-LWADCNet	DLMNN	MSSO-ANFIS	T-RNN
Miss rate (%)	6.13	14.6	93.1	63.26
RS	15.6	49.3	12.6	56.2

Statistical Analysis

The suggested model is statistically analysed using a tenfold cross-validation procedure. Ten distinct subsets, referred to as folds, [28], arise for every dataset. Both the normal and deviant sample distributions are equally included in each fold. The classifier undergoes training on nine folds in total, and it is tested on one fold in total. Ten times in all, the experiments are conducted for each testing subgroup [29].

Table 2 Using 10-fold cross validations, the CKD dataset's performance was assessed.

Number of rounds	**Accuracy**	**Recall**	**FPR**	**Precision 1**	**Precision 2**	**AUC**
1	94.66%	97.64%	97.69%	94.69%	97.64%	91.36%
2	91.36%	96.34%	97.69%	97.64%	95.36%	97.16%
3	97.63%	96.79%	97.69%	93.64%	94.63%	97.66%
4	94.69%	97.64%	91.03%	96.39%	95.67%	97.64%
5	97.69%	94.26%	91.79%	97.16%	96.69%	95.46%
6	97.65%	94.69%	97.64%	97.69%	97.64%	96.16%
7	91.32%	97.68%	96.36%	91.36%	96.34%	98.36%
8	96.36%	97.69%	94.66%	91.36%	97.64%	99.36%
9	97.63%	97.69%	97.64%	97.46%	90.16%	99.46%
10	99.36%	94.69%	96.17%	94.69%	97.69%	91.33%
Mean	98.66%	98.649	98.661	93.649	97.975	0.49772
SD	0.59	0.97	0.64	0.97	0.58	0.64

The average recall, precision, accuracy, AUC, and FPR of the data are assessed. Table 2 shows the results of the ten-fold cross validation.

The median quality measure attained in every session is shown for that round.

The last two rows of Table 2 provide the standard deviations and mean value for every outcome parameter [30].

CONCLUSION

Using the EO-LWAMCNet approach, the technique makes real-time predictions of kidney and cardiac disorders. The MATLAB library was implemented to accomplish the technique. The CKD and KD statistics provide validation for the technique. The accuracy, MCC, and F-score measures used in the testing procedures using the MSSO-ANFIS, T-RNN, and DLMNN techniques are employed to determine the method's economy. The suggested model's accuracy is 94% and 93.5% on two distinct datasets. Furthermore, the approach displays the greatest MCC and The F1 score values. As a result, the technique is effective in anticipating chronic illnesses including renal and cardiac problems. Although our model performs optimally, we want to improve it by evaluating it with additional image-based sets and reducing its execution time. Furthermore, we want to use a real-time dataset to forecast several illnesses that are airborne in the near future.

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