AUTOMATIC MEDICAL DISPATCHER WITH DYNAMIC TELE-MONITORING SYSTEM

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Abstract; Recent advancements in information technology have improved the design and development of disease prediction systems significantly. The disease prediction system is useful in diagnosing diseases by analyzing medical data. In this digital world, disease prediction systems are extremely important, especially during pandemic situations when physicians are in high demand andpeople are unable to reach hospitals to monitor and diagnose their health conditions. Many medical expert systems and disease prediction systems have been published in recent years. Still, there is a gap for people to have an effective disease prediction system to predict a patient's disease and severity level at the right time. Predicting the impact level of disease in the human body is considered one of the most difficult issues nowadays due to the increase in voluminous medical data with various new symptoms.

1. INTRODUCTION

1.1 HEALTHCARE MANAGEMENT

Nowadays people are exposed to many health issues due to their sedentary lifestyles. Healthcare management is an important task today due to the rapid growth of diseases and the advent of new symptoms of the old diseases. People are not getting medical attention on time due to inefficient medical facilities and most healthcare organizations cannot meet the medical demand of the public. Prediction of disease is also another important issue with healthcare management due to the formation of unusual symptoms which is about various diseases. An effective healthcare system is needed to provide better disease prediction and treatment with minimized costs. Due to the advent of unusual symptoms and an increase in the voluminous data of patients with various diseases, predicting the impact level of disease in the patient's body is considered one of the most difficult issues nowadays. Recent advancement in information technology has changed the way healthcare management is carried out and documented.

The World Health Organization (WHO) has identified that heart, diabetic and cancer diseases are deadly causing more than 12 million causalities in the world. Comparatively, this number is high in all countries, especially in developing countries. According to a statistic, there is a causality happening every 30 seconds due to any one of the above-mentioned diseases. Diagnosing these diseases is necessary today and it is also a challenging task for the health care department of each nation. Diagnosing the disease is vital because patients are not aware of the symptoms which fail to monitor the disease levels and health conditions

1.1.1 IoT in Healthcare

The Internet of Things (IoT) is a network of physical objects such as desktops, Laptops, Smartphones Tablets, etc. These Objects are embedded with sensors, software, and other technologies to communicate and exchange data with other devices and systems over the internet. Remote monitoring and disease prediction in the healthcare sector is now possible with IoT-enabled devices, which can keep patients safe and secure while also inspiring physicians to provide superior treatment. In healthcare IoT devices are rapidly integrated with AI and ML into disease prediction systems and process the medical data for efficient diagnosis of diseases. Furthermore, IoT-enabled disease prediction and remote monitoring of patients have a huge effect on reducing consultation time, minimizing healthcare costs, and improving disease prediction accuracy

IoT undeniably changes the healthcare industry by redefining the space of devices and human involvement in the delivery of healthcare solutions. The following are some of the main benefits of IoT in healthcare:

• Improved Treatment: It allows doctors to make evidence-based, well-informed decisions while providing complete accountability.

• Cost Savings: IoT allows for real-time patient tracking, reducing the number of unnecessary doctor visits, hospital stays, and readmissions.

• Rapidly Diagnosis: Using continuous patient monitoring and real-time data, doctors can diagnose diseases at an early stage, even before major symptoms occur.

• Preventive Medical Care: Continuous health monitoring allows for the provision of proactive medical treatment.

• Drug and Medical Equipment Management: In the healthcare sector, handling medications and medical equipment is a big challenge. These are efficiently handled and utilized by connected devices, resulting in lower costs.

Data created by IoT devices not only aids in efficient decision-making but also ensures that healthcare operations run smoothly with fewer system costs. IoT device uses sensor data, which helps medical practitioners understand sensitive circumstances more quickly and effectively also patients can be better informed about their symptoms and progress. Pulse-oximeters, electrocardiograms, thermometers, fluid level sensors, and Sphygmomanometers (Blood pressure), etc. are examples of IoT in healthcare sensors that are beneficial for analyzing the current patient condition

1.2 NON-COMMUNICABLE DISEASES (NCDs)

The diseases which are not communicable directly from one person to the other person are called non-communicable diseases. NCDs are connected with the way a person or group of people survives called a lifestyle disease. WHO recognized non-communicable diseases including heart, diabetes, cancer, chronic lung, and stroke (WHO Report, 2018). According to

the WHO non-communicable disease profile released inthe year 2018, non-communicable diseases causes nearly 70% of death around the world, among them 82% i. e. 16 million individuals prematurely deceased before the age of 70 years. These NCDs are generally caused by four major risk factors improper and unhealthy diet, lack of physical activities, abnormal weight, smoking, tobacco usage, alcohol abuse, stress, age, family medical history, heritage, and personal circumstances.

1.2.1 Heart Disease

Heart disease denotes any condition which affects the functionalities of the heart. Heart disease is categorized by different causes such as Coronary artery and vascular disease, Heart rhythm disorders (arrhythmias), Structural heart disease, and heart failure. Among them, coronary artery and vascular disease will happen when the arteries of a heart are blocked. This is a common heart disease and causes chest pain (angina). In addition, vascular disease is a problem with blood vessels that affect blood circulation and heart functionality. Heart rhythm disorders (arrhythmias) occur because of less heartbeat which affects the blood circulation. Structural heart disease refers to abnormalities of the heart's functionalities including its valves, walls, muscles, or blood vessels near the heart.

The WHO predicted that heart disease is a deadly disease and also identified the death rate in the world as around 120 lakhs. The number of death cases of heart disease is high in all countries, particularly in developing countries including India, Sri Lanka, Nepal, Pakistan, etc. Now, this life-threatening disease affects the adult with maximum death rate and increased the unpredicted fatality throughout the world. An analysis expressed that one person meets a heart disease death every 40 seconds in the United States (Bengio et al. 2013). Heart failure will happen due to high Blood Pressure (BP) and other serious symptoms which is the last stage of the disease leading to fatal. The major symptoms of heart disease are including high BP, high cholesterol, chest pain, and Sleep apnea. Heart diseases are dragonized and categorized based on individual lifestyle, family medical history, and medical health reports. Medical health reports are evaluated with the following reports Electrocardiogram (ECG), cardiac catheterization, cardiac Computerized Tomography (CT) scan, cardiac Magnetic Resonance Imaging (MRI), stress test, and Holter monitoring.

1.2.2 Diabetes Disease

Diabetes mellitus is commonly referred to as diabetes. Diabetes is a metabolic disease that causes high blood glucose. The insulin hormone supplies sugar to body cells from the blood which gives energy to humans. When the cells do not make enough insulin the person is identified as diabetic. If diabetes with high blood sugar is untreated, it will damage the nervous system, eyes, kidneys, and other organs. Generally, diabetes is classified into the following types prediabetes, gestational diabetes, type 1 diabetes, and type 2 diabetes. Among them, Type-2 diabetes is more severe than Type-1 diabetic disease. Autoimmune disease is said to be type 1 diabetes, which affects pancreas cells where insulin is generated. When the human body becomes insulin resistant and sugar builds up in the blood indicates type 2diabetes. During pregnancy, the blood sugar level is increased which indicates gestational diabetes. Prediabetes is a condition identified with high blood sugar above the normal level. According to the World Health Organization report, around four times of people were affected by diabetics between 1980 and 2014. In these statistics, the number of adult patients increased from 4.7% to 8.5%. Specifically, the 5% of patients are increased in the last one and half decades and it also increasing rapidly in high-income countries. Moreover, it causes major issues including heart attack, stroke, blindness, and kidney failure. Due to this reason, the death rate of diabetes is 16 lakhs in 2016. In addition, 22 lakh people lost their lives in 2012 due to high blood glucose that occurs before the age of 70 (WHO Report, 2021). Common diabetes symptoms include increased thirst and hunger, weight loss, blurry vision, frequent urination, and fatigue. Diabetes is associated with major complications such as heart disease, nephropathy, retinopathy, hearing and vision loss, skin infections, depression, dementia, etc. Diabetes can be diagnosed by doctors with the help of blood tests which includes fasting plasma glucose measures and hemoglobin A1C test.

2. RELATED WORK

A literature review in the context of a disease prediction system helps identify the issues, complexities, and importance of existing works. Also, it supports identifying suitable methodologies, tools, and datasets. This chapter provides an exhaustive review of various research works already done in the direction of healthcare management, disease prediction system, data mining, machine learning, deep learning, feature selection, and classification.

2.1 REVIEW OF HEALTHCARE MANAGEMENT

Nazar et al. (2020) conducted an investigation and discovered that diabetes, hypertension, and cholesterol levels have a clear relationship with COVID-19 severity. Furthermore, they discovered the virus is strongly linked to other dissociative disorders such as cancer, stroke, and kidney-related diseases. Finally, researchers advised extreme caution for COVID-19 patients, whose reports have been linked to cancer, stroke, and kidney disease. They have also identified several risk factors for poor COVID-19 outcomes, such as patients being elderly, having a smoking history, or having any other clinical condition. Moreover, they suggested treatment options be investigated further to provide optimal care and ensure better outcomes for patients suffering from these comorbidities. Camilla et al. (2020) declared a few suggestions to handle the current issues in the healthcare domain. The main aim of this work is to facilitate the learning strategy while introducing healthcare applications. This analysis applied a qualitative method by conducting reviews and pointing out the necessity. Phoutsathaphone et al. (2020) conducted a systematic review for synthesizing the various healthcare articles and identified the guidelines on the diabetes healthcare system which increases the competency Abbas et al. (2019) conducted a review of 202 published articles and identified 85 high-ranked articles that are relevant to the decision-making process on healthcare datasets. These articles were categorized into 9 major applications including healthcare technology, medical equipment management, and healthcare services. Moreover, in this survey, the ranking has been done by the categorization of various aspects including the decision-making and application areas. The various healthcare applications applied many decision-making approaches that are evaluated and ranked according to the service quality of healthcare and medical service applications. Waleed et al. (2019) suggested some guidelines to manage the diseases and handle the medical professionals through the heart failure expert committee which is comprised of thirteen specialists who are chosen from both private and public sectors. The committee finalized the

guidelines and disputes for managing critical situations in the disease diagnosis process in Saudi Arabia. Chun-Song et al. (2017) developed many methods to prevent heart disease especially cardiovascular he also improves the healthcare for non-communicable diseases. Gorunescu (2015) conducted an extensive survey about healthcare management using Machine Learning techniques which include the SVM, Genetic Algorithm (GA), Neural Networks, and nearest neighbor. These are applied for the diagnosis of the deadliest diseases like heart, cancer, and diabetes diseases.

2.2 REVIEW OF DISEASE PREDICTION SYSTEM

Debarpita et al. (2020) designed a framework that adopts a rough set aware lattice to represent the knowledge in a medical expert system that is overcoming the issue of redundancy and inconsistency. Their framework provides a flexible method to express the diverse possibilities among the disease symptoms. Mantim et al. (2020) proposed three methods that are applied for implementing Dr. Flynxz's Ailment Prediction and allergy management approaches. The experimental results represent the performance enhancement in terms of prediction accuracy. The system has been used to predict diseases by using the fuzzy inference system which applies the Mamdani-Sugeno type.

Oyelade et al. (2018) developed an input generation model which addresses the drawbacks via the inference creation process, the lexicon of breast cancer disease, rules, and natural language processing. Their method feeds the input to the inference engine that has rules and ontology. Finally, they prepared a list of tokens and used them in the expert system to diagnose breast cancer. Their expert system achieved better prediction and also generates additional input data. SiqiQiu et al. (2018) described the IF…THEN rules for representing the data incompleteness, vagueness, and non-linear casual relationships by assigning the degrees to all the possible values of the universe consequently with time interval-based weights. They have proposed an evaluation-based system to perform modeling and risk assessment processes with extended rules. Finally, they have applied their system to predict the possibilities of two different use cases.

Ramiro et al. (2017) developed a fuzzy logic incorporated a medical expert system to assist physicians in the process of predicting nephropathy control with type-2 diabetes. This expert system was designed using the practical guidelines and the knowledge provided by experienced medical doctors. Moreover, this system considers the blood glucose level, uric acid, age, serum creatinine, dyslipidemia, and hypertension for prediction. After being experimented with many times, they achieved more than 93% prediction accuracy and also, they proceeded the treatment successfully and cured them. Even though, they have failed to estimate the failure stages of patients.

Gwo-Haur et al. (2006) developed a time scale-based method for collecting medical data from experienced physicians. Their method consumed considerable time, based on the considered disease symptoms in various periods. Finally, they have proved that their expert systems have achieved greater performance than the conventional knowledge acquisition approach. Lenka et al. (2001) explained the various medical expert systems that apply intelligent rules. The various datasets such as diabetes, cancer, and heart diseases are applied for evaluating the different expert systems andachieving better prediction accuracy. They have considered the improved methodologies and effective steps to

diagnose the diseases.

2.3 REVIEW OF DATA MINING

Abbas et al. (2020) conducted an experimental study on the real medical dataset that was collected from 136 cancerous patients by using the data mining algorithms including Multi-layer Perceptron (MLP), ANN, SVM, Classification & Regression Tree (CRT), Logistic regression and C 5.0. The dataset contains details including smoking history, hypertension details, and blood pressure at the time of admission for the aged people. The algorithms achieved better classification accuracy. Heudel et al. (2019) developed a new data analytics model by incorporating data mining algorithms along with Natural language Processing (NLP) to categorize the data effectively. This model achieves better results and reached the performance limits. Heudel et al. (2019) analyzed the prognostic factors over elder women's treatment records as advanced treatment by applying the data mining algorithms.

Dominic et al. (2015) investigated the disease severity of chronic diseases by applying the IC9 diagnostic codes. For identifying the disease severity, various data mining algorithms are applied and gathered the heart and diabetes disease types. The system analyzes and identifies the relationship between the human anatomic methods such as circulatory, nervous, renal, musculoskeletal, neoplasm, and repository systems that are all identified as human anatomic methods. The disease severity level has been identified by using human anatomic methods. Baiju et al. (2015) applied data mining techniques to analyze the clinical data including diabetes research with the standard epidemiology and health services. Even though, the issues are necessary to be resolved by applying the mining techniques to medical research. Jesmin et al. (2013) investigated the health factors of heart disease in human beings. This work applies ARM and intelligence techniques for identifying the factors from the University of California Irvine (UCI) machine learning repository dataset that is utilized to make decisions on patient health records.

Gloria et al. (2008) aimed to evaluate the health resource utilization in particular lung cancer-affected people. The data mining algorithms were applied with the propensity score for varying predictive capability. The analysis shows the use of data mining techniques to handle complex and huge volumes of publicly used lung cancer data. End of the analysis, it is demonstrated that the model combines the Decision Tree and Artificial Neural Networks which provides better prediction accuracy.

2.4 REVIEW OF MACHINE LEARNING

Joshi et al. (2020) conducted an extensive review of the ML applications that are available for diagnosing various diseases. The review explained the different kinds of medical diagnosis systems that use ML algorithms for performing classification. The major objective of the review is to supply detailed information about the role of ML and AI in disease diagnosis. Finally, this review provides a lot of information to the practicing physician and also assists to evaluate the ML algorithms in the process of disease diagnosis through the prediction result on the disease dataset. Saurabh et al. (2020) conducted an extensive analysis of the machine-learning approach along with the datasets such as D1 and D2. Among them, D1 considers conjunctivitis, diarrhea, stomach pain, cough, and nausea-related data and D2 contains the standard dataset called WebKB4. The machine learning algorithms namely the Radial function incorporated SVM, MLP, and the Random Forest (RF). Finally, they achieved

97% as the highest accuracy in their experimental results. Moreover, they also showed the memorization process and tested it in the direction of maintaining stability and reliability. Sabrina et al. (2019) applied many machine learning algorithms with the adaptation of non-linear support vector curves on the Radial Basis Function (RBF) algorithm along with an optimized Grid search method and obtains more than 95% accuracy on heart disease dataset that is a set of records collected in more than two years. Mahdieh et al. (2018) described the different ML methods which are available with advanced techniques like data analytics and deep learning on IoT. In addition, the characteristics of IoT data are also applied to find the different approaches such as IoT with data analytics and data streaming analytics. In addition, deep learning along with data analytics is capable of achieving reasonable accuracy on medical datasets. Kohli & Arora (2018) applied various classifiers to classify the datasets such as cancer, diabetes, and heart diseases. A feature selection method was incorporated as a backward model by applying the value test. The experimental results expressed the strength of the ML on various medical datasets. Enas (2018) investigated the widely applied ML algorithms to predict various life threaten diseases such as heart disease and cancer diseases. The ANN, k-NN, DT, and ARM were applied for performing the classification process and analyze the results. This algorithm has achieved a prediction rate between 70% - 100% accuracy and still, it is not sufficient for the current world.

3. METHODOLOGY

3.1 INTRODUCTION

The use of disease prediction systems in hospitals and other healthcare facilities has increased dramatically and portable disease prediction systems based on new technologies are now a major concern for many countries around the world. IoT has aided the advancement of healthcare from face-to-face consultations to telemedicine, it has a huge effect on reducing consultation time, minimizing healthcare costs, and improving disease prediction accuracy. In IoT-based disease prediction systems sensor data can help medical practitioners to understand sensitive circumstances more quickly and effectively, also patients can be better informed about their symptoms and progress. In healthcare IoT devices are rapidly integrated with AI and ML into disease prediction systems and process the medical data for efficient diagnosis of diseases.

The current research scenario has limitations over high dimensional and complex datasets of diseaseprediction systems. To fulfilling the research gap, a novel disease prediction system is proposed in which novel feature selection algorithms and deep learning models are used to predict heart, diabetes, and cancer diseases. Here, feature selection algorithms are used to identify the optimal features that are helpful for the classifiers to make abetter decision with reduced computation time. Moreover, deep learning models are used to predict diseases more accurately than the other existing methodologies. The research framework which covers architecture, workflow, and performance evaluation metrics is framed in this chapter in detail

3.2 PROPOSED DISEASE PREDICTION SYSTEM ARCHITECTURE

The architecture of the proposed disease prediction system comprises five important modules namely user interface, medical database, feature selection, classification, and disease prediction modules as shown in Figure 3.2.

3.2.1 User Interface Module

The user interface module serves as a bridge between the user and the disease prediction system. It collects patient data using IoT devices like desktops, laptops, smartphones, and tablets, along with necessary sensors like pulse-oximeters, electrocardiograms, thermometers, fluid level sensors, smartwatches, and Sphygmomanometers, and converts the user request into query format. The user query contains the patient details such as name, age, gender, contact information, sensor data, symptoms of diseases, and medical reports. To process the real-time streaming features, it employs the sliding window protocol. With the help of the user interface module, the formatted user's query or request is to be forwarded to the disease prediction module. An additional important task of the user interface module is to collect classification results from the disease prediction module and sends them to the users as a disease prediction report.
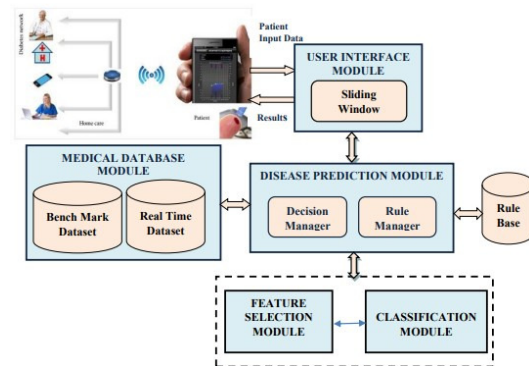

Figure 3.1 Architecture of Proposed Disease Prediction System

3.2.1.1 Sliding window

A sliding window is used to process continuous queries over data streams. When data elements arrive in a continuous stream, a sliding window answers the queries for the most recently arrived N elements. The proposed work handles the streaming features using a self-adapting sliding window protocol which is used to handle the overflow of streaming data. It adjusts the sliding window size according to the streaming feature arrival rate using sliding window threshold parameters. The features arrival rate is frequently calculated by the self-adapting protocol and updates the corresponding threshold values to change the window size (Dianlong et al. 2019). The Sliding Window Size (SWS) is calculated using Equation (3.1)

The sliding window selects the optimal features from streaming data in real-time using a heuristic function. The heuristic function provides information to search about the direction of an objective function used in the feature selection process. It offers a mathematical method for selecting relevant features from a data stream. It calculates the distance between current and optimal features and assigns heuristic values to streaming features based on feature information obtained from the feature selection module. The sliding window collects streaming data from IoT devices and sends it to the disease prediction module. The disease prediction module examines the required streaming data sliding window

3.2.2 Medical Database Module

The medical database module includes standard benchmark datasets as well as real-time streaming datasets. The standard benchmark datasets are heart, diabetic, and cancer disease datasets from the UCI Machine Learning Repository. Real-time

streaming datasets include data such as patient details, symptoms, and medical reports collected from patients via IoT devices. Furthermore, hospital data is collected and stored in real-time streaming datasets. All of these datasets have varying numbers of records, and each record in each dataset has a different number of features that are used to evaluate the proposed disease prediction system.

3.2.3 Disease Prediction Module

The disease prediction module has control over the entire architecture of the proposed disease prediction system. It analyzes and processes the queries received from the user interface module and sends the disease prediction results back to the user interface module. The major responsibility of this module is to train the model using all the possible combinations of available feature selection and classification algorithms. It does so by utilizing three important components as decision manager, rule manager, and rule base, which are used to perform various tasks for effective disease prediction.

3.2.3 Feature Selection Module

The feature selection module is responsible for performing data preprocessing effectively. Here, two operations such as feature subset generation and subset evaluations are performed to select the optimized feature set. In the feature selection module, three newly proposed feature selection algorithms are used such as EGWO-FSA, GBCOA, and IFSA. These algorithms have been applied for performing the feature selection effectively

In GBCOA, the binary cuckoo optimization algorithm is used to perform the subset selection operation, and the genetic algorithm is used to perform a subset evaluation operation to select the best optimal feature set. EGWO-FSA is applied for identifying the contributed features using an enhanced gray wolf optimizer. The IFSA algorithm is implemented by combining the Intelligent Conditional Random Field (ICRF) and the Linear Correlation Coefficient based Feature Selection (LCFS) algorithms called ICRF-LCFS. Here, features are grouped based on distance metrics. Then, the LCFS and ICRF are used to select the most significant features that are useful for making an effective decision on disease-affected records to improve classification accuracy.

3.2.4 Classification Module

The classification module categorizes the data according to the features extracted from the feature selection module. The classification module trains deep learning models such as novel C-RNN, new T-CNN, and the standard DBN for generating classification rules. In C-RNN, the convolutional layer is integrated with the classical RNN. It also incorporates the GRU cells with the recurrent layers to handle the time sequence data. In T-CNN, the temporal features are considered while deciding on the disease dataset. Moreover, the DBN is also incorporated in the classification phase for classifying the data effectively. The proposed classifiers in this module categorize the data as "normal," "susceptible," or "diseased," with the disease being either diabetic, cancer, or heart disease. Furthermore, the proposed classifiers can accurately predict the disease severity level.

3.3 WORKFLOW OF THE PROPOSED DISEASE PREDICTION SYSTEM

The sequence of operations involved in the proposed disease prediction system is illustrated in Figure 3.2. The user's query or patient medical reports will be sent to the decision manager through the IoT device. Rule manager generates nine classifiers such as EGWO-FSA & DBN, EGWO-FSA & C-RNN, EGWO-FSA & T-CNN, GBCOA& DBN, GBCOA& C-RNN, GBCOA& T-CNN, IFSA & DBN, IFSA & C-RNN, and IFSA & T-CNN by combining all possible combinations of proposed feature selection and classification algorithms. Also, the rule manager generates the rules by training all the classifiers using the available datasets. The rule manager stores and frequently updates the rules in the rule base with its new prediction accuracy.
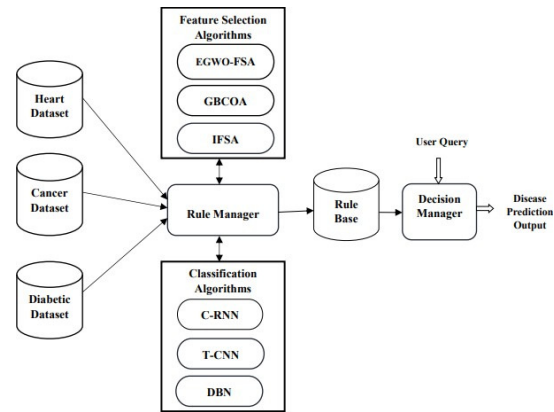

Figure 3.2 Workflow of Proposed Disease Prediction System

The rule base holds all rules generated by the rule manager. The decision manager will analyze the patient's data using the rules available in the rule base and selects the optimized rule with the highest disease prediction accuracy. The decision manager decides the input data and produces the optimized disease prediction output as a result for the user.

3.4 PROPOSED METHODOLOGIES

This research has introduced a new disease prediction system with the use of feature selection and deep learning algorithms. It has been carried out with three different techniques with different combinations of feature selection and deep learning algorithms. In the first technique, a disease prediction system is developed with the combination of the new Enhanced Grey Wolf Optimization-based Feature Selection Algorithm and Deep Belief Network (EGWO-FSA & DBN). The second technique is designed using the new Genetic Binary Cuckoo Optimization Algorithm and the novel Convolutional Recurrent Neural Network (GBCOA & C-RNN) for efficiently identifying diseases and their severity level. The third technique implements a novel disease prediction system that has been developed using the Incremental Feature Selection Algorithm and Convolutional Neural Network with Temporal features (IFSA & T-CNN) for predicting diseases with less computation time.

3.4.1 Disease Prediction System Using GBCOA and C-RNN

this technique introduces a novel disease prediction model to predict diabetes, cancer, and heart diseases. This model applies a newly developed Genetic Binary Cuckoo Optimization Algorithm and the Convolutional-Recurrent Neural Network to predict the diseases. The GBCOA algorithm is used to select the most significant features that are applied for enhancing the classification accuracy of the C-RNN model. The CRNN model combines the convolutional and recurrent layers to perform both sequential processing and multiclass classification for effective disease prediction. The Recurrent layer of the C-RNN model consists of multiple GRU with two types of gates namely relevant and update gates to handle the temporal features.

3.4.2 Disease Prediction Using IFSA and T-CNN

In this technique, a novel disease prediction system for predicting diseases such as diabetes, heart, and cancer is proposed. This methodology incorporates a newly proposed feature selection algorithm called Incremental Feature Selection Algorithm and a temporal-Convolutional Neural Network to predict the diseases. The proposed IFSA algorithm combines the ICRF and LCFS methods. In IFSA, the ICRF is used to group the features based on their distance from one another. The correlation coefficient value is computed after grouping the features using the related formulae, and it also selects the most relevant and useful features to improve classification accuracy. Then, LCFS was used to evaluate and select the cluster with optimized features that are useful in making an effective decision on disease-affected records.

4. CONCLUSIONANDFUTUREWORK

This research work has been proposed and implemented as three different methodologies as Enhanced Grey Wolf Optimization-based Feature Selection Algorithm with Deep Belief Network, Genetic Binary Cuckoo Optimization Algorithm with Convolutional-Recurrent Neural Network, and Incremental Feature Selection Algorithm with Temporal Convolutional Neural Network. The overall architecture is made up of various feature selection and classification algorithms that have been proposed. Finally, it is used as a disease prediction system, capable of predicting fatal diseases such as diabetes, heart disease, and cancer.

In the EGWO-FSA & DBN methodology, a new disease prediction system has been proposed and implemented with the incorporation of IoT and Deep Learning techniques. Here, a new feature selection algorithm called EGWO-FSA is implemented to achieve better classification accuracy through DBN. This disease prediction system, predicts disease and its severity level according to the inputs that are collected through IoT devices. Experiments were carried out to evaluate the proposed methodology using datasets from heart, diabetes, and cancer diseases. On various types of heart, diabetes, and cancer datasets, this methodology achieved an overall prediction accuracy of 95.05%. Furthermore, it categorizes patient information based on disease types and severity levels.

In the GBCOA & C-RNN methodology, a new disease prediction model has been developed and implemented to predict the diseases such as heart, diabetes, and heart diseases. This new model applies a newly developed GBCOA algorithm and C-RNN model to predict the disease. The major contributions of this work are the introduction of the feature selection algorithm with a deep learning model which combines the convolutional layer and recurrent layer to perform feature reduction and sequential. Moreover, it is useful for selecting the contributed attributes that are applied to improve classification accuracy. In addition, the application of the proposed GBCOA feature selection algorithm and Convolutional - Recurrent Neural Network model with multiple GRU cells is useful for performing the multiclass classification on disease datasets. The proposed disease prediction model achieved 95% overall disease prediction accuracy on heart, cancer, and diabetic disease datasets. Finally, this disease prediction model proved as better than other models in terms of better prediction accuracy with less computation time for performing the classification.

For making decisions on the records, time is taken into account and applied to the soft-max layer of T-CNN. At the end of the classification process, the normal records and disease-affected records in the heart, diabetic, and cancer disease datasets can be identified. Furthermore, this disease prediction system is useful for learning about the disease and its severity level. This technique has been tested using standard medical datasets such as diabetes, heart, and cancer disease datasets. The experiments have been conducted for evaluating the model and achieved 97% accuracy as an overall prediction accuracy for the diabetic, heart, and cancer datasets. Finally, this technique is proved as better in terms of prediction accuracy than the existing disease prediction model which uses deep learning algorithms and other classification algorithms. The proposed disease prediction model is taken less time for performing classification.

In this system, the user's query or patient medical reports will be sent to the decision manager through an IoT device. Rule manager generates nine classifiers such as EGWO-FSA & DBN, EGWO-FSA & C-RNN, EGWO-FSA & T-CNN, GBCOA& DBN, GBCOA& C-RNN, GBCOA& TCNN, IFSA & DBN, IFSA & C-RNN, and IFSA & T-CNN by combining allpossible combinations of proposed feature selection and classification algorithms. Furthermore, the rule manager generates the rules by training all of the classifiers with the available datasets. The rule manager stores and frequently updates the prediction performance metrics scores of the rules in the rule base. All rules generated by the rule manager are stored in the rule base. The decision manager must identify the best classification rule for better prediction based on the user's request.

Each algorithm is capable of performing well on a variety of datasets. Even though all possible feature selection and classification algorithm combinations performed well on the diabetic dataset, heart dataset, and cancer dataset, with good prediction accuracy and less computational time. The precision, accuracy, recall, and f-measure score of the proposed algorithms are used to assess their disease prediction accuracy. According to user data, the best combination of feature selection and classification algorithm is identified for effectively predicting diseases. Finally, the proposed disease prediction system predicts diseases and their severity levels with minimal computation time. The proposed model achieved an optimized disease prediction accuracy of 97.8%, 98.4%, and 97.5% on heart, diabetic, and Cancer datasets respectively. Also obtained was the reduced computation time of 0.41sec, 0.89sec, and 0.53 sec on heart, diabetic, and Cancer datasets respectively.

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