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Prediction of symptoms and diseases using machine learning algorithm for health care recognition system

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***Abstract*---**As a result of their surroundings and lifestyle choices, people nowadays are affected by a wide range of ailments. As a result, early disease prediction becomes crucial. Doctors, on the other hand, struggle to make accurate forecasts based on symptoms. Accuracy anticipating disease is the most challenging challenge. Machine learning plays a key part in anticipating in order to solve this difficult issue. To tackle this problem, machine learning plays a key role in disease prediction. Medical science creates vast amounts of data every year. Early patient care has benefited from the good medical data analysis because of the growing volume of data in the medical as well as healthcare professions Disease data are used in data mining to uncover new pattern information in massive volumes of medical data. Based on the clinical condition, we created a broad illness prognosis. We apply the machine learning techniques Gated Recurrent Unit (GRU) and ANFIS to accurately forecast sickness. The collecting of disease symptoms is required for disease prediction. For an accurate prognosis, this general disease prediction considers the person's lifestyle and checkup information. GRU has a greater accuracy for general disease prediction than the GRU algorithm, at 97.8 percent. Furthermore, because GRU trains and tests on the UCI repository dataset, it consumes more time and memory than ANFIS. Because it provides a range of libraries and header files that make the process more precise and exact, the Anaconda notebook is the finest tool for implementing Python programming.

***Keywords*---**GRU, ANFIS, machine learning, health care, disease prediction.

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Introduction

Classification techniques, as opposed to individual classifiers, are commonly employed in the medical industry for categorizing data into different classes depending on specified restrictions. Diabetes is a disease in which the body's ability to produce the hormone insulin is impaired, resulting in incorrect carbohydrate metabolism and high blood glucose levels. Diabetes is defined by high blood sugar levels.. High blood sugar levels generate symptoms such as thirst, hunger, and frequent urination. Diabetes, if left untreated, can cause a plethora of consequences. Two of the most significant consequences are diabetic ketoacidosis and nonketotic hyperosmolar coma [1]. Diabetes is a crucial dangerous health problem in which the amount of sugar material cannot be managed. Diabetes is influenced not only by a number of characteristics including height, weight, genetic factor, and insulin, but the most important component regarded among all aspects is sugar concentration. Complications can only be avoided if they are identified as soon as feasible [2].

Diabetes is a condition that arises in the human body when glucose levels in the blood are unusually high, i.e., sugar levels are abnormally high. Glucose, a crucial component of carbohydrates, is present in the bloodstream and acts as the primary source of energy for our bodies, derived from the food we eat. The pancreas secretes insulin, a hormone that collects glucose from food and allows beta cells to absorb and convert it into energy [3]. Unfortunately, the human body does not always create enough insulin or does not make any insulin at all. Nonetheless, despite the fact that diabetes is a potentially fatal disease, it is manageable by early detection, right diagnosis, competent medical care, and simple lifestyle changes [4].

Recent medical developments have seen the use of data mining techniques to analyse medical datasets in order to assist clinicians in the early detection of diseases, ultimately saving human lives. Diabetes is a challenging disease to diagnose because it affects a wide population all over the world, and clinicians have relied on medical records to make diagnoses for millennia. These datasets are collected on a continuous basis and include a variety of Patient-related factors like age, personality, illnesses, sugar levels, heart rate, blood glucose levels, bodyweight, and etc [5]. Data mining techniques are used to extract and use those most useful data to support in right diagnosis because the accessible information is huge. Machine learning algorithms such as Nave Bayes, Support Vector Machines, Decision Trees, Neural Networks, Ensemble approaches, but many are applied to disease-related data to aid in the correct diagnosis [6].

The UCI Diabetes Training Dataset was extracted using the suggested ANFIS machine learning classification algorithm in this research. Rather than taking into account all of the diabetes-related features in the dataset, this methodology was utilised to extract only those having the highest likelihood of predicting the disease's incidence. As a result, when compared to ANFIS, ANFIS is a more efficient and trustworthy strategy for diabetics drug planning aims. other ways, and the results achieved for each algorithm are compared based on the accuracy metrics.

The remainder of this paper is organized as follows: Section II discusses other literature surveys, Section III discusses how the proposed methodology works, and Section IV discusses the final results obtained. Section V discusses the paper's conclusion.

Literature Survey

Data analysis and prediction of future behavior using datasets is beneficial in a variety of resources, including human health. Human resources are one of the most important and everlasting components of this planet. As digital technology expands in every sector, it is also expanding medical facilities to detect and predict diseases such as diabetes. A specific number of studies have been conducted by analyzing and predicting future diseases based on datasets provided by the patient's health records. We discovered some of the best methods for prediction and analysis through additional records and work on medical technology.

In [7] concluded that the WEKA tool was one of the greatest for classification of data mining. According to them, an accuracy rate of 74.28 percent on the breast cancer dataset and SMO has an accuracy rate of 76.80 percent on the diabetes dataset. They used a selection process on various algorithms and techniques in [8] to improve the accuracy of different algorithms. Following feature selection, they obtain (Decision Tree) DT is 82.22 percent, (Logistic Regression) LR is 82.56 percent, Random Forest is 84.17 percent, Nave Bayes is 84.24 percent, and SVM is 84.85. In [9], they used k-nearest neighbor and a genetic algorithm to analyze big data for the forecast of coronary sensitivity disease. They concluded given system allows them to predict diseases at an early stage, and that this method helps to improve the medical field by making it easier for physicians to analyze and predict. In [10], they develop a prediction model that uses data from wearable devices to diagnose cardiovascular issues. They achieved an accuracy of 87 percent using the Logistic Regression Model. Furthermore, by measuring under the ROC curve, an AUC score of 80% is obtained in [11]. After running the entire algorithm on the same dataset, they discovered that the proposed technique outperformed all other classifiers in terms of performance and prediction.

Table 1. Related work on various approaches of analysis and predicting future diseases

Sl:No:	References	Techniques	Drawbacks
1	[12]	They present clinical features that, when combined with the proper data cleaning method.	However, experimental results show that the proposed methods did not perform well in terms of slope and survival predictions.
2	[13]	It was discovered that SVM performed the unsurpassed in the ailment forecast in terms of accuracy.	SVM outperforms Simple Cart in terms of overall performance in predicting diabetes disease. As a result, the shown to be

			insufficient for further modal.
3	[14]	In this paper, two data mining methods, Nave Bayes and the J48 algorithm, are compared for accuracy and performance on training medical datasets.	The conclusion derived from the J48 and Nave Bayes evaluation results was that Nave Bayes results did not satisfy the best accuracy of prediction of analysis on the datasets.
4	[15]	It consists of a disease prediction system that employs machine learning and artificial neural network concepts.	It does not provide complete data functionalities from datasets.
5	[16]	The analysis of a outsized amount of information from a patient using data mining as well as machine learning algorithms, resulting in the use of big data technologies and tools.	It concludes that we are unable to predict all diseases at an early stage using this predicted system, and that this system cannot be used in the medical field for physicians to easily analyze and predict disease.
6	[17]	Using conventional algorithms, this study proposed general illness forecast based on patient symptoms.	It is difficult to analyze and extract diabetes disease data.
7	[18]	Using KNN and CNN, this study proposed general illness forecast based on patient symptoms.	They do not provide accurate predictions to satisfy doctors.
8	[19]	This study focuses on the selection of techniques and algorithms for experimentation analysis using multiple heart disease datasets.	Decision Tree has an accuracy of 82.22 percent.

Because Chronicle Diseases advance slowly, it is vital to diagnose them early and give appropriate therapy. As a result, developing a decision model that may aid it is critical to diagnose chronic diseases and predict future patient outcomes. While there are several methods in the field, the study focuses on ML forecasts used in CD diagnosis, emphasising the significance of this research. We conducted a thorough review of the literature on several cutting-edge prediction models in this study, and our key contribution is to construct comparative analysis method to suggest model categorization. In compare to conventional data analysis approaches, this review paper will be able to identify potential findings that increase the performance of patient data, as well as study of specific features associated with Ml techniques in medical care.

Proposed Methodology

The primary goal of this paper is to identify classification algorithms that will most accurately predict the presence of diabetes in patients for early detection and treatment. Figure 1 depicts the model diagram for the proposed work. It is possible to predict more than one disease at a time using a multi disease model prediction. As a result, users do not need to navigate through a plethora of models in order to predict diseases. It will save time, and by predicting multiple diseases at once, the mortality rate may be reduced.

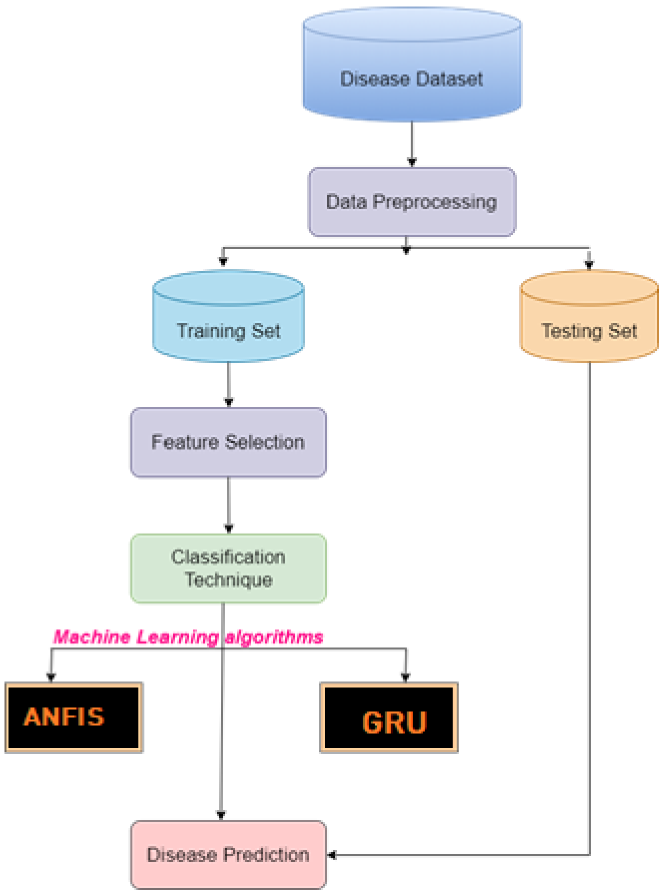

Figure 1: Proposed System Flow chart

Preprocessing

Certain preprocessing techniques on network inputs and targets may improve the efficiency of neural network training. The network input processing routines convert inputs into a more network-friendly format. The raw input normalization method has a substantial impact on data preparation for training. Developing the neural network models would have been extremely slow without this normalization. There are various kinds of data normalization. It's used to normalize the information for each additional input in the same value range, removing the bias from one character to the next within the neural network. By 'is training procedure for every feature on another scale, data standardization can help to reduce training time. It is especially useful in modelling situations with complicated inputs [20].

Feature Selection

Feature selection, also referred as Variable Sampling [21], is a data preparation strategy in data mining that is commonly used for data reduction by removing irrelevant and superfluous attributes from every dataset [22]. This technique also increases data comprehension, provides for improved data visualisation, decreases learning algorithm training time, and improves prediction performance. The incorporation of symmetric uncertainty (SU) resulted in the discovery of an optimum threshold value. The least spanning tree was created when symmetric uncertainty was applied (SU). The suggested algorithm's findings were compared to those of other algorithms has established that best of them [23].

Classification

CNN

To forecast the matching SDS, most known algorithms use a single spectral observation [3]. Nonetheless, several photos taken at different periods in the same quadrat may aid in improving the model's prediction accuracy. As a result, a system that can deal with time-series imaging is required. For non-linear time-series processing, recurrent neural networks (RNNs) are a good choice [45]. The RNN has as shown in Figure 5. The RNN can be unfolded as the right component when dealing with time-series data. Equation (5) and Equation (6) can be used to determine the output and hidden layers, respectively.

$y_t = g(s_t * w_{hy})$ (1)
$f(x_t * w_{sx} + S_{t-1} * w_{ss})$ (2)

The RNN approach is plagued by the gradient vanishing/exploding problem, Regardless of its reputation as a nonlinear function approximator and its ease of implementation. During the training phase, gradients are computed from of the output nodes to the RNN's first layer. The gradient of the last few layers would become minimal if the gradients were far from one as a result of several multiplications. If the gradients are more than 1, on the other hand, the gradients will become very huge. As a result, when it reaches the initial layers of RNNs, the gradients can become practically zero or quite significant. As a result, the first layer's weights will not be changed during the training procedure. As a result, simple RNNs might not be appropriate for some complex tasks. In this study, a GRU-based technique for dealing with the vanishing gradient problem of a typical RNN [39] is proposed.

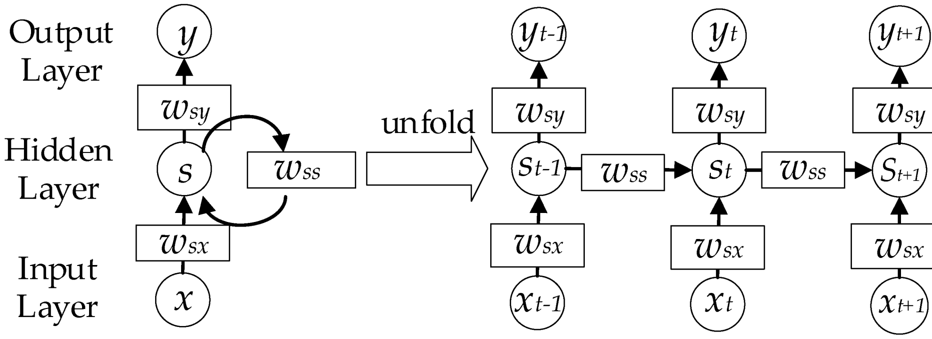

Figure 2. Structure of the GRU

ANFIS

Related to all aspects of fuzzy inference and artificial neural networks, neuro-fuzzy inference algorithms are classified into two categories. In the first scenario, fuzzy inference is incorporated into in the artificial neural network; however, fuzzy inference is not incorporated into in the artificial neural network in the second situation. Fuzzy reasoning, which would be classified into the Mamdani method [25] and the Takagi–Sugeno method [26], is one of the methods of the second sort that has been extensively researched as a method for incorporating artificial neural networks. At the end of the rule, the Mamdani system has become a fuzzy set, whereas the Takagi–Sugeno system would become a first-order linear function of the input parameter. When employed with artificial neural network optimization method, the Takagi–Sugeno system, for instance, is computationally more efficient, adaptive to establishing rules, and has the benefit of maintaining output space continuity. For the reasons stated above, we chose the Takagi–Sugeno scheme in the Proposed method to generate and infer rules.

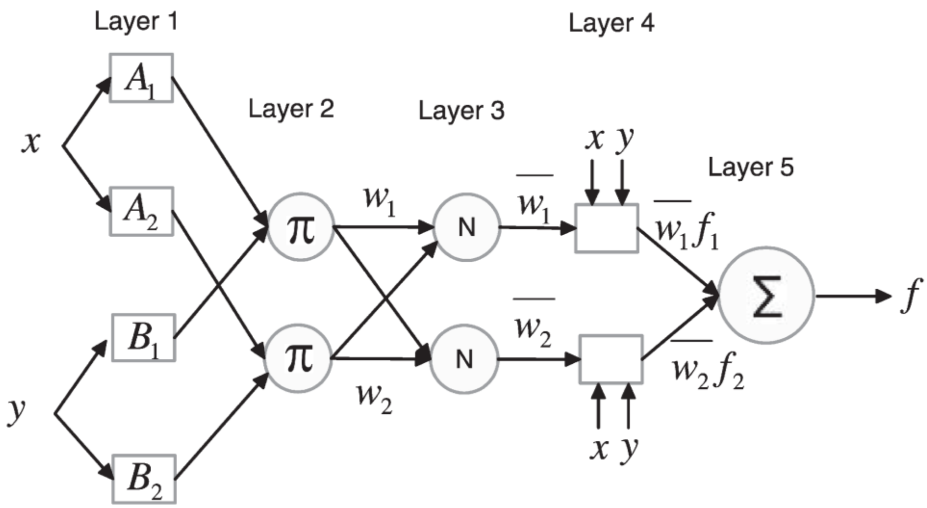

Figure 3. ANFIS classification architecture

The ANFIS model was introduced as a sort of Neuro-fuzzy inference system in [27]. The ANFIS model may optimally estimate the following included in the membership functions plus output for giving actual output using the ordinary least (LSE) plus back propagation (BP) algorithms. To describe the fuzzy inference method succinctly, a model composed of n Takagi–Sugeno norms having two inputs or one output, and the outcome of the first linear model, is employed.

Results and Dicussion

The proposed methodology is tested on the Diabetes Dataset (UCI) [28], which is obtained from the UCI Repository. This dataset contains the medical information of 768 female patients. The disease prediction algorithms are fed a set of symptoms provided by the user. The symptoms can be selected from a drop-down menu on the platform, and the algorithms will analyse them in the back-end. The user-selected symptoms are then analysed by each of the algorithms, with the output being the mean accuracy. The output is then used as weights in the ensemble classifier for those algorithms. Accuracy, Specificity, Precision, and Recall are the evaluation metrics used [29].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{(TP)}{(TP+FP)} \quad (3)$$

$$Recall = \frac{(TP)}{(TP+FN)} \quad (4)$$

$$Specificity = \frac{(TN)}{(FP+TN)} \quad (5)$$

Table 2: Shows the Description of Diabetes Attributes Dataset [29]

Sl:No:	Attribute Name	Description
1	Preg	integer of times pregnant
2	Plas	Plasma glucose absorption a 2 hours in an oral glucose tolerance examination
3	Pres	Diastolic blood pressure(mmHg)
4	Age	Age(in years)

Table 3. Summarization of Prediction methods with Performance for Preg

Prediction Techniques	Accuracy	Precision	Recall	Specificity
SVM [30]	0.69%	0.67%	0.62%	0.60%
KNN [31]	0.71%	0.70%	0.68%	0.61%
Decision Tree [32]	0.80%	0.78%	0.72%	0.69%
GRU [33]	0.89%	0.87%	0.83%	0.70%
Proposed ANFIS	0.97%	0.95%	0.94%	0.92%

Table 4. Summarization of Prediction methods with Performance for Plas

Prediction Techniques	Accuracy	Precision	Recall	Specificity
SVM [30]	0.74%	0.71%	0.68%	0.63%
KNN [31]	0.75%	0.72%	0.66%	0.60%
Decision Tree [32]	0.76%	0.74%	0.69%	0.61%
GRU [33]	0.80%	0.78%	0.71%	0.67%
Proposed ANFIS	0.96%	0.94%	0.93%	0.91%

Table 5. Summarization of Prediction methods with Performance for Pres

Prediction Techniques	Accuracy	Precision	Recall	Specificity
SVM [30]	0.76%	0.73%	0.70%	0.67%
KNN [31]	0.77%	0.74%	0.70%	0.67%
Decision Tree [32]	0.80%	0.77%	0.73%	0.69%
GRU [33]	0.84%	0.80%	0.78%	0.75%
Proposed ANFIS	0.95%	0.94%	0.93%	0.92%

Table 6. Summarization of Prediction Techniques with Performance for Age

Prediction Techniques	Accuracy	Precision	Recall	Specificity
SVM [30]	0.66%	0.63%	0.60%	0.58%
KNN [31]	0.70%	0.69%	0.64%	0.60%
Decision Tree [32]	0.75%	0.70%	0.68%	0.65%
GRU [33]	0.80%	0.77%	0.74%	0.70%
Proposed ANFIS	0.95%	0.93%	0.92%	0.91%

Table 7. Summarization of CPU Time test for all classification algorithms

Prediction Techniques	Running Time (ms)
SVM [31]	5.63 ms
KNN [32]	3.75 ms
Decision Tree [33]	2.19 ms
GRU [34]	0.94 ms
Proposed ANFIS	0.36 ms

Conclusion

The great majority of the world's population is affected by diabetes. Diabetes is a disease that can only be controlled, not cured. Diabetes that is not well controlled can cause complications, which can lead to a range of other chronic conditions. As a result, it's vital to have early detection, successful treatment, and proper diabetes management. Diabetic nerve disorders can impact the heart and, as a result, the heart rate. In this article, we employ UCI data (extracted from a variety of electric signals) to accurately detect diabetes. This is the first study that we are aware of that uses deep learning to detect diabetes using UCI data. The ANFIS classification system had a 96.7 percent accuracy, which is the highest accuracy in the automated identification of diabetes using UCI to date. For benchmark comparison with the proposed ANFIS classification, explicit feature extraction and the use of classical classifiers are necessary. Clinicians will be able to diagnose diabetes more precisely with the suggested approach. As mentioned in the Results section, a bigger input dataset than the one utilised in this study can be fed into the suggested architecture to see if accuracy can be improved further.

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