International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Diabetic Monitoring System using Learning Automata based Fireworks Algorithm and Dynamic Brain Storm Classifier

Manivannan D [1], Kavitha M [2]

Submitted: 22/07/2022 **Accepted**: 25/09/2022

Abstract: In this paper, we propose a new evolutionary classifier that is capable of achieving better prediction results than the conventional classifiers and the earlier evolutionary classifiers that are available in the literature. To reduce the severity level of diabetes and also predict the disease levels as Type-1 and Type-2. Moreover, a new evolutionary classifier incorporating a diabetic monitoring system is proposed to monitor the diabetic disease by using the newly proposed brain storming classification algorithm that applies the existing Enhanced Fireworks Algorithm and Brian Storm Optimization method. This work improves the structure of the evolutionary classifier by enhancing the classification accuracy. Feature selection is necessary to handle the huge datasets. So, the proposed model extracts the necessary features first by applying the newly proposed Learning Automata and Fireworks Algorithm based Feature Selection Method to identify the most important features that are helpful to enhance the prediction accuracy. This work is evaluated by using the different diabetic datasets from the UCI Repository and hospital datasets by conducting various experiments and is also proved to be better than other models by considering the evaluation metrics, namely precision, recall value, f-measure value, and decision accuracy.

Keywords: Diabetic disease, Evolutionary Classification, Feature Selection, Brian Storm Optimization and Enhanced Fireworks Algorithm.

1. Introduction

Diabetes mellitus (DM) is characterized by abnormally high levels of glucose in the blood. When it increases the glucose level in the blood after a meal, it releases the hormone insulin. Moreover, it stimulates the insulin of muscle and fat cells to remove glucose from the blood and also stimulates the liver to metabolise the glucose level, which causes the glucose level to decrease from a normal level. Generally, people with high glucose levels may have the reason that insulin is not produced properly and it is not made at enough levels. Type 1 diabetes affects only 5% of people and is an autoimmune disorder, while type 2 diabetes affects 95% of people and is linked to obesity [39]. In addition to those, various factors are contributing to the high blood glucose levels in these individuals. DM is the oldest disease that was first reported in Egypt before 3000 years. Afterwards, the type-1 and type-2 classifications are clearly identified, and these are described clearly in the year of 1988. Living with Type-2 DM is dangerous for humans, as it causes both long-term and short-term complications that lead to death.

The Fireworks algorithm was developed by Tan (2010) for performing the explosion process and also initializing the solution. Here, the explosion process acts as a stochastic search process around the fireworks. The fireworks algorithm initializes the n number of fireworks in a specific search area and it evaluates to finalize the number of explosions and sparks. At the end, the remaining fireworks are considered as candidate fireworks, and the sparks are identified as new fireworks. Researchers are increasingly interested in using the fireworks algorithm to solve real-world optimization problems in fields such as networks, vehicle congestion, robotics, information retrieval, and layout issues, among others. The researchers are enhancing the performance of the fireworks algorithm by introducing an enhanced version of the algorithm. Among them, Zheng et al (2013) developed the Enhanced Fireworks Algorithm with five changes to overcome the drawbacks, and Zheng et al (2014) improved it further as a dynamic fireworks algorithm to achieve better performance.

Learning automata (LA) (Narendra et al 1974) is also one of the Machine Learning (ML) techniques that is used as an optimization software for performing the effective optimization process automatically. It maintains a probability vector where every component indicates a reward probability and also updates the actions. Moreover, the LA is used to identify the most suitable action from a number of actions to apply by default to the environment. The LA accepts the vectors based on their own methodology. For this purpose, many Particle Swarm Optimization (PSO) algorithms are combined together by using LA to select the important characteristics of PSO. In this work, a novel LA-aware Fireworks Algorithm (LAFA) is developed to obtain a reasonable number of sparks through the LA and fireworks algorithms that are helpful for assigning the promising fireworks that ensure the capability of strong local search.

Classification of data is done by Machine Learning (ML) algorithms widely and it is also done by Deep Learning (DL)

[1] Department of CSE, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India- 600062
ORCID ID : 0000-0002-9095-9287

[2] Department of CSE, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, India- 600062
ORCID ID : 0000-0002-4050-5850
Corresponding Author Email: mani02.ceg@gmail.com

algorithms recently. For performing the classification process, the various ML algorithms include the k-Nearest Neighbor (KNN) algorithm, the Decision Tree (DT) algorithm, Naïve Bayes (NB) classification method, the Artificial Neural Network (ANN), the Support Vector Machine (SVM), etc. Similarly, deep learning algorithms such as the Convolutional Neural Network (CNN) algorithm, Deep Belief Network (DBN) algorithm, Long Short-Term Memory (LSTM) algorithm, and Recurrent Neural Network (RNN) algorithm are also available for performing effective classification on various kinds of datasets. Even though the available techniques failed to obtain the exact classification result due to their failure to utilise the optimal features.For this purpose, various evolutionary algorithms, including PSO, Ant Colony Optimization (ACO) algorithm, Genetic Algorithm (GA), Ant Bee Colony Optimization algorithm, fireworks algorithm, and brain storm optimization algorithm are available for enhancing the classification accuracy by recommending the necessary exact features.

The feature selection process is an important task in the process of data preprocessing and it is capable of improving the classification accuracy in various ML and DL algorithms on various kinds of datasets. The optimal feature set alone is not able to improve the accuracy of the classifiers and also to simplify the structure of the classifiers. In this direction, the evolutionary classifiers are capable of finding the most useful features and classification results. In this work, a new feature selection technique is introduced for enhancing the structure of evolutionary classifiers using the brain storm optimization method. The major contributions of this work are below:

1. To propose a new feature selection algorithm for identifying the most useful feature to predict diabetes and its severity levels.
2. To propose a new Brain Storm Optimization aware classification algorithm for predicting and categorizing diabetes disease severity levels.
3. To incorporate temporal constraints for making effective decisions over the patient record before moving to the next level, that means from type-1 to type-2.
4. We achieved better classification results quickly over the standard bench mark dataset and hospital dataset.
5. proved to be better than the existing systems in terms of precision, recall, f0measure and prediction accuracy.

The remainder of this article is organized as below: Section 2 goes into detail about the work that is available in the areas of data preprocessing, feature selection and optimization processes, learning automata, and various classifiers. Section 3 explains the overall architecture of the proposed heart health monitoring system. Section 4 discusses the proposed work with the necessary backgrounds, steps, and explanation. Section 5 demonstrated the results and also discussed the necessary justification. Section 6 concludes this work by highlighting the contributions and their achievements according to the performance metrics and also suggests future work in this direction.

2. RELATED WORK

Many disease prediction systems and healthcare applications have been developed in the past by various researchers to assist patients and physicians to predict the disease level (Shreshth et al 2020, Bide and Padalkar 2020, Romany et al 2021, Yuxin et al 2021, Hamidreza et al 2021). Among them, Tarik et al (2004) developed a hidden Markov model aware of an automatic diagnosis system to predict the apnea syndrome disease. In their system, they generated rules by considering probabilistic principles. Moreover, they have developed a simulated annealing method to train the hidden Markov model. In addition, they have translated the input parameter values into two different states, such as pathophysiological and physiological. Their method considered and measured the various activities such as respiratory activity, brain activity, cardiac activity and the oxygen levels for detecting sleep apnea disease and measuring the levels online and off-line. Finally, they have proved that their model is better than the existing systems in terms of prediction accuracy. Sannasi et al (2013) explained the intelligent feature selection algorithms and classifiers that are available in the literature and widely used for predicting intruders and anomalous users in various applications.

Sethukkarasi et al (2014) proposed a new Fuzzy Cognitive Map with the incorporation of temporal features to predict heart disease and also monitor the disease severity level. Their system achieved better accuracy in terms of prediction than the conventional classification algorithms. Ganapathy et al (2014) proposed a new disease prediction system which applies the newly proposed Fuzzy Temporal Min-Max Neural Classifier with Particle Swarm Optimization for predicting diabetes diseases, heart diseases, and cancer diseases effectively. Their system performs better than the fuzzy Min-Max classifier with Genetic Algorithm and Fuzzy Cognitive Map and other neural classifiers. Cermakova et al. (2015) conducted a thorough examination of the impact of Alzheimer's disease on heart failure.

Ali et al (2018) conducted an extensive review of the computational intelligence techniques that are applied in the medical field for categorising the techniques. Moreover, they have presented the methodologies and techniques with merits and demerits in their work. The demerits are resolved by using computational intelligence. They improved the accuracy of SVM, Fuzzy SVM, Genetic aware SVM, and Artificial Immune System aware SVM by incorporating computational intelligence. Sundaravadivel et al (2018) developed a novel IoT aware monitoring system that works as an automated system in the healthcare system. They have proposed a new five-layer neural classifier and the Bayesian classifier to monitor the nutrition level in food and have also gathered the nutrition facts and ingredients. Han et al (2018) developed a new data mining technique aware model to predict type 2 diabetes mellitus. Their model consists of two phases, such as improved K-means clustering and regression methods. The proposed model achieved more than 3% greater accuracy than the existing systems.

Lakshmanaprabhu et al (2019) developed a new IoT and Cloud-aware Medical Expert System to predict the chronic kidney disease severity level. They have collected the patient data from hospitals that is stored in the cloud database with the necessary medical records that are collected from the UCI Machine Learning Repository. Moreover, they have applied deep neural networks to predict kidney disease. They have also applied a feature selection method that incorporates the PSO to enhance the classification accuracy. Finally, they have achieved 99.25% accuracy in prediction. Simeon et al (2019) conducted a comparative analysis by considering the ML/DL algorithms' performance according to the classification accuracy. Mohsin

Raza et al (2019) developed a new ML-aware disease monitoring system to monitor the disease and also analyze the Magnetic Resonance Imaging (MRI) scans by applying DL and monitor the daily activities of the patients. They have achieved 95% prediction accuracy, which is greater than the standard classifiers available on the market. Kanimozhi et al (2019) developed a new cancer prediction system to predict the cancer disease by using a new fuzzy rule-based classifier and also obtained better performance than the existing systems in terms of prediction accuracy.

Muhammad et al (2019) proposed a new model using the standard ML algorithms for predicting Alzheimer's Disease that categorizes the necessary stages and also finds the distinguishing feature. Finally, they have achieved a best prediction accuracy of 88.24%. By analyzing magnetic resonance imaging (MRI) using deep learning techniques, Raza et al (2019) developed a new ML-based disease diagnosis and monitoring system for predicting Alzheimer's disease. Lin et al. (2020) created a new prediction system that uses speech data as input and effectively analyses the collected data to predict disease-affected people.

Farman Ali et al (2020) proposed a new healthcare application that incorporates the feature fusion technique and an ensemble DL approach for predicting heart diseases effectively. In their work, they have combined the extracted features from benchmark data and live data in their feature fusion technique, eliminating the irrelevant data using the information gain value of the features and finalizing the useful features to reduce the computational complexity. Moreover, they have applied weightage to the features by applying conditional probability. In the end, the ensemble deep learning method trained the data and predicted the heart disease effectively and achieved 98.5% accuracy as a prediction accuracy. Lin et al (2020) developed a new method which applies the spectrogram attributes that are extracted from speech data that is helpful in understanding the disease level. They have applied speech data that is gathered from elderly people and also applied ML methods to identify Alzheimer’s disease more effectively than Logistic Regression. Ismail et al (2020) proposed a novel CNN aware method to detect and recognize the pattern behavior of the disease according to the Pearson Correlation Coefficient method. In this work, the authors selected the most important health-related factors and also conducted the correlation coefficient analysis for identifying the regular patterns of heart disease, and obtained better prediction accuracy than other ML algorithms with low computational complexity.

Khan et al (2020) proposed a novel prediction system to predict heart disease by applying the modified Deep CNN that is applied to categorize the data as normal and abnormal. Their system conducted a comparative analysis with logistic regression and the other deep neural classifiers. Finally, their system achieved 98.2% prediction accuracy, which is better than the existing classifiers. Pan et al (2020) proposed a novel enhanced DL-aware CNN technique to assist the patient's improved heart disease diagnostics. They have used IoMT to make effective decisions on the input records that are used by the physicians for safeguarding patients and also preventing disease growth. Their model is proven to be better than the available deep learning techniques by achieving 99.1% prediction accuracy. Samah (2020) developed a new patient monitoring system with the incorporation of IoT and a deep learning modified neural classifier for diagnosing heart disease. Their system works based on three different techniques, such as authentication, encryption, and classification. They have applied the existing hashing algorithm called SHA-512 to perform the authentication process. The Advanced Encryption Standard is used for performing the encryption process, and it decrypts the secured data by using the same. Finally, the deep learning based modified neural classifier was used for categorizing the data as normal and abnormal and obtained a prediction accuracy of 95.87%.

Mazin Alshamrani (2021) conducted a survey about the health care applications that are implemented on IoT and also evaluated the relevant technologies to understand and predict patient records using various sensors. At the end of their survey, they have highlighted the major issues and the advantages that can be recommended as future work. Mohammed Farsi (2021) created an LSTM as well as ensemble learning techniques such as AdaBoost, Stacking, XGBoost, Random Forest, and Bagging. For conducting experiments, they have generated live data by using IoT sensors from patients and also validated the proposed method by applying the standard benchmark dataset and the newly generated live dataset. In the end, they have proved that their method is better than other ensemble methods according to the obtained prediction results.

Bhat et al. (2021) presented a risk prediction tool that uses machine learning algorithms to predict asthma disease. Their tool uses mobile health applications and IoT. Generally, the peak expiratory flow rate is calculated by using external devices like peak flow meters. In their work, they have identified the correlation values. The results were displayed with three colors such as green, yellow, and red, which represent normal, medium, and risk, respectively. The CNN is used to perform the mapping process in this case. Finally, they have proved to be better than the available methods in terms of prediction error rate and accuracy. Pothuganti et al (2021) developed a new IoT aware greenhouse model which is responsible for performing the monitoring of the disease, alerting the patients, storing the data in a cloud database safely and performing the disease prediction process. Their system monitors the environmental characteristics such as humidity, soil moisture and temperature to guarantee better production. At the end, they detected the crop diseases by analyzing the leaf pictures.

Kohzoh et al (2021) developed a system to predict Parkinson's disease by analyzing the features, including heart beat rate, effectively and achieving better prediction and detection accuracy. Nanda Gopal et al (2021) focused on the methodologies available in the literature for detecting breast cancer early using ML and IoT. The major aim of their work is to explore the ML algorithms in the process of detecting breast cancer and also obtain above 96% prediction accuracy with less error rate. Yuxin et al. (2021) developed a novel non-invasive diagnosis technique for detecting the disease early by using a new technology and an immersive and advanced human-computer interface is also proposed for predicting the disease effectively. Shuangshuang et al. (2021) proposed a diagnosis system to predict Alzheimer’s disease that applies a new feature extraction and classification which combines the ANN and Bayesian Classifier.

Forum et al (2022) developed a new cloud for healthcare to monitor the health status of the registered users in their cloud using ML techniques and cloud. In their work, they have predicted the presence of the disease using ML algorithms, namely K-NN, SVM, Regression, Decision Trees, and Neural Classifiers. They achieved around 96% as their best result and also conducted five folds of cross validation. Bhushankumar and Devan (2022) presented a new adoptive learning framework that works in an incremental manner for predicting the water quality using IoT sensors with the incorporation of genetically aware SMOTE and hyperparameter tuned deep learning classifiers. They have achieved 99.34% accuracy as their best. Sujith et al. (2022) developed a new system with the incorporation of blockchain technology and deep learning algorithms for effectively analysing healthcare data to obtain better performance by achieving better accuracy even considering the multiple parameters. Their application is helpful for patients to know the status of their disease level. All the available work is not fulfilling the current requirements in terms of efficiency and prediction accuracy. This work proposes a new smart healthcare system that applies a newly proposed wrapper-based feature selection and the hyper parameter tuned deep learning classifier.

3. ARCHITECTURE OF PROPOSED MODEL

The architecture of the proposed heart health monitoring system is demonstrated in figure 1, which contains ten important components, namely: datasets, user interaction module, Decision Manager, Rule Manager, Rule Base, Feature Optimization Phase, Evolutionary Classification Phase, Diabetic Level Prediction Phase, and severity level predictor.

The decision manager serves as a coordinator, coordinating all of the architecture's components. The user interaction module Interacts with the users and the datasets for the purpose of extracting the data from the various datasets and the user's requests. The rule manager is useful for the decision manager to retrieve the rules from the rule base according to the user's requests. The decision manager performs the feature selection and optimization processes through the feature optimization phase that applies the enhanced version of firework's algorithm and learning automata-based brain storm optimization method. The decision manager performs the disease prediction process by applying a newly proposed classification algorithm. Final results are to be conveyed to the respective users through the user interaction module.

4. PROPOSED WORK

This work proposes an evolutionary classification model for obtaining required prediction accuracy according to the current requirement and it is better than the existing classifiers. In this work, an Enhanced Learning Automata based Fireworks Algorithm (ELAFWA) is proposed for performing effective feature selection. Moreover, a new dynamic brain storming classification algorithm incorporated Enhanced Fireworks Algorithm (DBSOFA) is also proposed for performing effective classification with optimization. Finally, the proposed model is proved to be as efficient and effective as the existing disease prediction models.

4.1. Background

This section contains the necessary background information for the various algorithms, such as the Fire Works Algorithm (FWA),

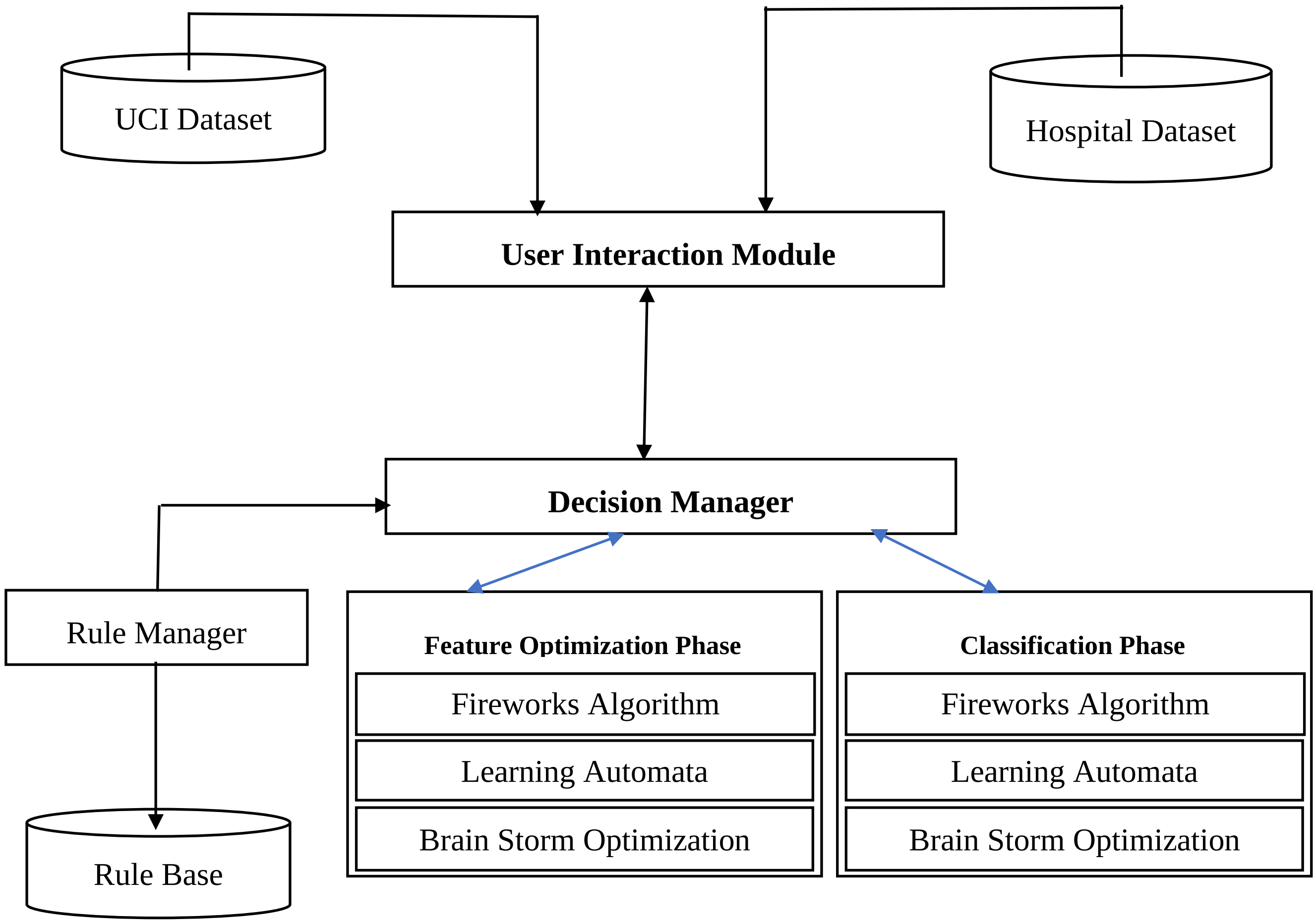

Figure 1. Overall System Architecture

Guiding Spark FWA (GFWA), Learning Automata (LA), and LA-based FWA (LAFWA).

4.1.1. Fire Works Algorithm

The Fireworks Algorithm is a swarm intelligence method, and it is short for FWA, that explores a number of solutions by identifying a group of points that are randomly confined by a few distance metrics in the hopes that they are capable of promising the yield that allows and also concentrates more on the searching process. The FWA describes fireworks that exploit the fireworks processes. Here, sparks are pointing out the specific points and it is out of the explosion. Every location of the spark is also considered until they reach the exact point and the optimal solution. In addition, the variable $x_j$is satisfying the expression $f(x_j) = y$ and it continuous until a specific spark that is nearbyx_j. This method starts with choosing 'n'number of locations that are in initial fireworks. Then, the number of sparks and the respective locations of their sparks are determined based on the proximity towards the optimal location.

4.1.2. Guiding Spark Fire Work Algorithm

The Guiding spark FWA (GFWA) is helpful for resolving the minimization problem without sacrificing generality:

$$\min f(x) \qquad (1)$$

Here, the variable x is a vector value. The strategy is used to explore the GFWA, which considers the temporal features. Based on the workflow of GFWA, every firework's sparks are demonstrated as below:

$$\boldsymbol{\lambda_i} = \hat{\boldsymbol{\lambda}}.\frac{\max_j\left(f(X_j)\right)-f(X_i)}{\sum_j\left(\max_k(f(X_k))-f(X_j)\right)}, \qquad (2)$$

Where the equation (2) demonstrates a parameter to control the sparks. According to this calculation, a FWA along with a low-level fitness value is generating more sparkling values. Second, for each firework from dynFWA, GFWA uses a dynamic explosion amplitude updating approach. Every firework explosion is also determined as below:

$$A_i(t) = \begin{cases} A_i(t-1)\cdot p^{+} & if \quad f(X_i(t)) - f(X_i(t-1)) < 0 \\ A_i(t-1)\cdot p^{-} & otherwise \end{cases} \qquad (3)$$

The ithframework's position and explosion at tthgeneration which is represented by Ai(t) and Xi(t), respectively. The explosion spark generation process for the ith firework is done by using the standard steps that are elaborated by Tan et al (2010). Guidance Vector: In GFWA, a guiding vector (GV) mechanism is proposed. A guiding vector is constructed using a group of high-quality sparks and a group of low-quality sparks. A firework is guided by the GV to travel further. It's worth noting that each firework produces a guiding vector. Moreover, the i-th firework's GV is designated "I" and is determined as follows from its exploding sparks:

$$\Delta_i = \frac{1}{\sigma\lambda_i}\left(\sum_{j=1}^{\sigma\lambda_i} s_{i,j} - s_i, \lambda_i - j + 1\right) \qquad (4)$$

Where, the variable σ is consider as a control parameter for the proportion of chosen explosion sparks and it is also denoted the spark of the ith firework along with the jth lowest fitness score. As seen in, a guiding spark (GSi) is created by adding a GV to the ith firework (5).

$$GS_i = X_i + \Delta_i \qquad (5)$$

The major objective of the vector for the guiding process is to identify the position of the spark and the relevant fitness value for the best individual value. Here, it calculates the number of sparks, the explosion amplitude, generates the sparks, and evaluates all the necessary sparks. Finally, it returns the position and fitness value.

4.1.3. Learning Automata

Learning Automata (LA) is a variable structure that represents in the form of quadruple $\{\alpha, \beta, P, T\}$, where $\alpha = \{\alpha_1, \alpha_2, \ldots \alpha_r\}$ is a group of activities; $\beta = \{\beta_1, \beta_2, \ldots, \beta_s\}$ is a group of input values; $P = \{p_1, p_2, \ldots, p_r\}$ is also a probability vector of various activities and the variable T is a pursuit method for updating the probability vector value, $P(t+1) = T(\alpha(t), \beta(t), P(t)$. The famous pursuit method DP_{RI} is developed in the works [18,19] that enhances the probability value of the expectedactivity that is optimal and also decreases other values. The pursuit method is demonstrated as below:

$$p_w(t+1)=max(0,p_w(t)-\Delta) \qquad w\neq I \qquad (6)$$
$$p_i(t+1)=\sum p_w(t)-p_w(t)-p_w(t+1)+p_i(t) \qquad (7)$$

where the i-th action is the best one. [20] proposes another well-known pursuing scheme, DGPA, that enhances the probability related activities along with larger reward estimations that are better than the currently identified activity when decreases the probability of others. The following is a description of it:

$$p_w(t+1)=max(0,p_w(t)-\Delta) \qquad p_w<p_i \qquad (8)$$
$$p_w(t+1) = \frac{\sum p_i(t) - p_i(t+1)}{k} + p_w(t) \quad p_w \geq p_i \qquad (9)$$

Where the i-th action is the best one. Kohzoh et al [20] propose another well-known pursuing scheme, DGPA, which increases the state probability of actions with larger reward estimations than the current chosen action while decreasing the state probability of others. The following is a description of it:

$$p_w(t+1) = \max(0, p_w(t) - \Delta) \qquad (10)$$

$$p_i(t+1) = \frac{p_w(t) - p_w(t+1)}{\|Z(t)\|} + p_w(t), \forall i \neq w, i \in Z(t) \quad (11)$$

4.1.4. Brain Storm Optimization

The various evolution algorithms were introduced by various researchers in the past by considering the Brain Storm Optimization (BSO) that was presented by Shi [27] in the year of 2011. The BSO employs the clustering method for finding the local optimal value and then compares all of the local optimal values to find the global optimal value. That is identified as an exact method to resolve the high-dimensional method-aware problems with different peaks. Finally, the BSO method is also frequently applied in evolutionary classifiers. Individuals in the BSO method represent the potential problem solutions, and the various solutions are converged into multiple clusters. Through the evolution and fusing of individuals in clusters, new individuals are created. The steps of the BSO are described with three important steps such as the initialization process, regeneration population process and the new individuals are compared to the originals, and optimal individual solutions.

1.*Initializationprocess*: The 'N' number of individual solutions are identified in random manner and the fitness values are also computed for all.

2.*Regeneration population process:*When the enough solution is identified or the maximum number of iterations are identified then the following steps need to be done.

1)Solution clustering: The k-means algorithm divides N individuals into m clusters;

2) Developing new solutions: The individual from the clusters is to beselected randomly as new.

3) Selection of new solution: Consider the fitness values of the new and old solutions, and save the solution with the higher fitness value in the upcoming execution.

3. Identify the *Optimal individual from selected solutions*: Comparing the core persons in m clusters yields the global ideal individuals.

4.2. Feature Selection

Feature selection is an important and initial task in the process of data handling. Data preprocessing needs to be done effectively to obtain more prediction accuracy in a short span of time. Efficient and effective disease prediction systems are the most wanted in this fast world. So this system introduces a new feature selection algorithm called the Enhanced Learning Automata Based Fireworks Algorithm (ELAFWA) for identifying the optimal features from the datasets. This section explains in detail the proposed ELAFWA with the necessary equations and explanations.

4.2.1. Learning Automata based Fireworks Algorithm

The DPRI is modified in this work to make it more suited for our approach. It recompenses the predicted exactly required activity and also punishes others in the standard DPRI. The pursuit strategy, on the other hand, causes the state probability vector to rapidly converge, which is detrimental to the global search capability in the early stages of the search. Moreover, the best 'm' number of actions, along with the top one, will be rewarded in the m-DPRI. And as the search goes, m lowers linearly, eventually improving the local search ability. The following is a description of the updating strategy:

$$p_w(t+1) = \max(0, p_w(t) - \Delta), w \in [m+1, n] \quad (12)$$

$$p_w(t+1) = \frac{\sum_{m+1}^{n} p_i(t) - p_i(t+1)}{m} + p_w(t), w \in [1, m] \quad (13)$$

$$m=m\text{-}1 \quad if \quad g\%\frac{MG}{M}=0 \quad (14)$$

where the variable "m" indicates the initial number of m, the current generation number is represented by the variable "g", the variable MG indicates the maximum number of generations permitted, and M represents the step size. After the update, the vector probability is sorted to determine which of the'm' number of activities is to be awarded.

***4.2.2.* Assigning Sparks:**

In this research, LA is used to allocate sparks to pyrotechnics based on the state probability vector. More sparks will be generated by the firecracker with a higher chance. As the search progresses, the probability of the vector converges, and the promising fireworks emit the majority of the available sparks in the late search stage, giving the method a strong local search capability. According to the probability vector values p, n probability ranges P are constructed for initializing the sparks. The newly proposed ELAFWA initialises the sparks by applying the probability intervals 'P' in the procedure of assigning SPARKS.

$$P_i(t) = \left[\sum_{1}^{i-1} p_j, \sum_{1}^{i-1} p_j + p_i\right] \quad (15)$$

First, generate a random number between 0 and 1. Second, identify the probability interval for each value from the random values.

Eight different steps of the newly proposed Enhanced LAFWA method are listed below:

1. Initialization Process: Fireworks' velocities and positions are to be generated randomly. Next, assign the sparks equally to set up the state probability.

2. Sparks Assignment Process: Each spark is to be assigned to 'n' number of fireworks with a possible number of changes that are able to generate more sparks.

3. Explosion Process: The amplitude of each firework's explosion is determined by incorporating a hypercube, and sparks are to be generated in a consistent manner.

4. Guiding Sparks Generation Process: Generate the guiding spark by applying the equations (4) and (5).

5. Fireworks Selection Process: Examine the sparks' values and the guiding vector's fitness values. Find the best individual spark among the available sparks, including the guiding spark.

6. Update the Probability State: Sort the ‘p’ values and update it based on the equations (12) and (13).

7. Decrease the Linearly: Perform the linear decrement process of "m" using the equation (14).

8. Terminal Condition Checking Process: If the pre-defined termination conditions are met then, end the algorithm. Otherwise, move to step 2.

4.2.3. Learning Automata based Fireworks Algorithm

Input: Features

Output: Optimal features

Step 1: Initialize the fireworks as ‘n’

Step 2: Assign the initial probability value for $p = \left(1/_n, ..., 1/_n\right)$

Step 3: Find the fitness value for all the ‘n’ number of fireworks.

Step 4: Check whether the stopping condition is not satisfied

4.1 Initialize the sparks value according to the random value between 0 and 1 and the probability interval.

4.2 Find the explosion amplitude by using the equation (3).

4.3 Generate the sparks with necessary steps mentioned above.

4.4 Guiding spark to be generated by applying the formulae that are available in the equations (4) and (5).

4.4 Calculate the spark’s fitness value and the guiding vector value.

4.5 Choose the optimal one as the new framework.

Step 5: Update the p value by applying the equations (12) and (13) and also sort the p values.

Step 6: Perform the decrement process linearly for the m values by applying the formula available in the equation (14).

Step 7: Display the optimal fireworks.

4.2.4. Dynamic Brain Storm optimization-based Classification

The newly proposed Dynamic Brain Storm Optimization based Classifier (DBSOC) is explained in detail in this section. Generally, the proposed classifier works based on the evolutionary classification model. So, we can discuss the evolutionary classification model.

A. Evolutionary Classifier

The basic model for the evolutionary classifier is developed by [21], [22] and also explained in their work in detail. Generally, the given training dataset TD = (p1, q1), (p2, q2),... (pn, qn), where the variable pi = (pi1, pi2,... pid) denotes the i^{th} instance and the class label of the i^{th} instance is qi, as given in equation (16) for the "n" number of training datasets.

$$\begin{bmatrix} x11, & x12, & \cdots, & x1d, & y1 \\ x21, & x22, & \cdots, & x2d, & y2 \\ \cdots, & \cdots, & \cdots, & \cdots, & \cdots \\ xn1, & xn2, & \cdots, & xnd, & yn \end{bmatrix} \tag{16}$$

First, the weight vector W is represented as W = w1,w2,...,wd, the classification issue is viewed as an optimization issueto resolve the linear equations, such as Eq (17).

$$\begin{cases} w1x11 + w2x12 + \cdots + wdx1d = y1 \\ w1x21 + w2x22 + \cdots + wdx2d = y2 \\ \cdots \\ w1xn1 + w2xn2 + \cdots + wdxnd = yn \end{cases} \tag{17}$$

The W indicates the solution set which is capable of satisfying the equation. Let's assume that the linear equation's co-efficient matrix is P and the constant column vector is Q, as shown below:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nd} \end{bmatrix} \text{ and } Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{18}$$

The equation (17) is represented as P WT = Q [26]. R(P) is the rank of matrix P, while R(P, Q) is considered as a rank matrix (P, Q) (P, Q). In many situations, the ‘n’ number of instances exceeds the deadline ‘d’, and the equations are unrelated. As a result, it's possible that these equations are uncorrelated and that there is no solution that exists that satisfies all of them. Moreover, finding approximate answers to the following equation is all that is required to solve the classification problem:

$$\begin{cases} w_1x_{11} + w_2x_{12} + \cdots + w_dx_{1d} \approx y_1 \\ w_1x_{21} + w_2x_{22} + \cdots + w_dx_{2d} \approx y_2 \\ \cdots \\ w_1x_{n1} + w_2x_{n2} + \cdots + w_dx_{nd} \approx y_n \end{cases} \tag{19}$$

This work may determine the class label of instance xi using this set of approximation solutions, which is described as:

$$\begin{cases} y_1 - \delta \le w_1x_{11} + w_2x_{12} + \cdots + w_dx_{1d} \le y_1 + \delta \\ y_2 - \delta \le w_1x_{21} + w_2x_{22} + \cdots + w_dx_{2d} \le y_2 + \delta \\ \cdots \\ y_n - \delta \le w_1x_{n1} + w_2x_{n1} + \cdots + w_dx_{nd} \le y_n + \delta \end{cases} \tag{20}$$

Where, indicates a threshold which calculates and considers the label's error that is permitted to fall under the specific range. Moreover, the model's objective methods are demonstrated as an equation (21).

$$\min(f(W)) = \sqrt{\sum_{i=1}^{d}\sum_{j=1}^{n}(w_j * x_{ij} - y_i^2)} \quad (21)$$

To minimize the solution search space, we utilize Eq. (22) to estimate the upper and lower boundaries of the solution for initialization weight parameter population.

$$\pm\sigma \frac{\sum_{i=1}^{N} y_i}{\sum_{i=1}^{N}\sum_{j=1}^{d} x_{ij}} \quad (22)$$

where N represents the number of individuals in the population, d represents the dimension of the training set, and σ is used to adjust the control parameters of the boundary range. It is effective to control the search space in a certain range, but how to determine the search space well is our next research direction.

The feature subset population is then combined with the weighted parameters population. Each individual's fitness value was computed. The BSO algorithm's optimization objective function is the minimum error value (min(f(W)), and the fitness calculation approach is Eq (23).

$$f(W) = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{d}(w_j * x_{ij} - y_i^2)} \quad (23)$$

where n is the number of samples in the training set.

Second, using the k-means algorithm, N individuals are clustered into m, and the centre individuals are chosen from each cluster with the best fitness value. Finally, by comparing the centre members in each cluster, the ideal individuals are determined. We produce new individuals from the existing population of people if the ideal individuals are not satisfied.

The search area can be improved by clustering operations. However, after a large number of iterations, all solutions converge with high probability to a narrow search area. A disrupted cluster operation is added to the BSO algorithm to avoid being trapped in local optimums or premature convergence. A probability value P governs the disrupted cluster action. Create a random number between 0 and 1, and if it is more than P, create a random individual (with feature subset and weight parameters) to replace a central individual at random. Otherwise, new people will be created on the spot.

The method generates new individuals by randomly selecting clusters, and these individuals can be based on one or more existing individuals. According to this article, if the probability value P cluster is greater than 0.8, additional individuals are generated based on one existing individual. Otherwise, new people are created by combining the characteristics of many current individuals. The search area can be optimized if fresh individuals are formed in one cluster, and the algorithm concentrates on development capability. As a result, if more clusters are used to generate new individuals, the new individuals may be far from the initial cluster centre. In this situation, the algorithm places a greater emphasis on the ability to explore.

To create new individuals, the probability values Pone and Ptwo are utilized to regulate the random individuals. A random value is created for each cluster, and if the random value is bigger than the probability value, P, the central individual in this cluster is chosen for generating the additional individuals. On the other hand, to produce a new type of individual, a random individual who is non-central to the specific cluster is chosen. Eq. (24) and Eq. (25) describe the formation of new individuals at this time (25):

$$x_{new}^{i} = x_{selected}^{i} + \xi(t) * N(\mu, \sigma^2) \quad (24)$$

$$\xi(t) = \log sig\left(\frac{0.5 * \max_{iteration} - t}{k}\right) * rand() \quad (25)$$

where xi indicates the i[th] individual to be updated with the consideration of weight and subset, and xnewi indicates the i[th] new individual along with necessary parameters.

N(,2) are normal distribution random numbers; rand() is a procedure which creates random numbers between the range 0 and 1. Maximum number of iterations is also consider as an important input, while t is the current number of iterations. k is the coefficient that controls the logsig() function, which is used to modify the size of the search step in (t) and thus balance the algorithm's convergence pace. The logsig() transfer function is defined as Eq (26):

$$\log sig(\alpha) = \frac{1}{1 + \exp(-\alpha)} \quad (26)$$

The new individuals developed are based on two individuals for each of the two clusters chosen. The probability value P2 is compared against a random value created. If the random value is less than the probability value P2, we randomly select the central individual of two clusters to generate new individuals; otherwise, we randomly select the common individual of two clusters to generate new individuals. Two existing individuals, xselected1 and xselected2, are combined to form a new individual, with xselected1 representing the selected individual with feature subset and weight parameters in the first cluster and x selected representing the selected individual with feature subset and weight parameters in the second. The picked individual xselected can be written as in this situation:

$$x_{selected}^{i} = x_{selected1}^{i} * term + x_{selected2}^{i} * (1 - term) \quad (27)$$

where tem is a random number in the range of (0, 1), which is generated by the *rand()*.

Finally, the goal of the new individual selection is to keep those who are physically fit in the population. If the stop requirements are not met after generating new individuals, the individuals with greater functional fitness are saved to the next iteration through a selection technique. To ensure population variety, the approach of clustering, creating, and selecting new people is employed to introduce new individuals into the population. The steps of the proposed DBSOC are as follows:

4.2.5. Dynamic Brain Storming Optimization based Classifier

Input: Population size, Max_Clusters, Iterations_limit and Probability values.

Output:Classification accuracy

Step 1: Generate the individuals randomly with features

Step 2: While ($Current_{iteration} < Max_{iteration}$) do

2.1 Form m number of clusters using n individuals

2.2 Select the cluster head for all the clusters

2.3 If the random value of the individual is greater than the probability thengenerate a random individual and replace the cluster head randomly

2.4 Choose random values for generating new individuals.

2.5 Check whether the random values of a cluster are lessthan theprobability value of the cluster.

2.6 If it so, select the cluster head randomly by applying temporalfeature if the probability value of the specific individual.

2.7 Otherwise, choose any two individuals and fused by equation (27).

Step 3: Generate new individuals based on the selected individual by equation (24).

Step 4: Compare the old and new individuals and the individualswith smaller fitness values that are left from individuals.

5. RESULTS AND DISCUSSION

The newly proposed disease prediction model has been implemented using the Python programming language and it has also been tested by conducting various experiments in the WEKA tool. In this work, the standard data set called the University of California, Irvine (UCI) Machine Learning Repository that contains the diabetic disease dataset has been used as an input dataset and also to evaluate the disease prediction model. Generally, the prediction process plays a crucial role today in hospitals and physicians' offices due to the increase in different kinds of diseases. The first subsection of this section explains in detail the benchmark medical datasets that are used in this work for evaluating the proposed prediction system.

5.1. Evaluation Metrics

The proposed prediction model is evaluated by using the performance evaluation parameters such as precision, recall and f-measure. These values are calculated using the equations (28), (29) and (30).

$$\boldsymbol{Precision} = \frac{\boldsymbol{TruePositive}}{\boldsymbol{TruePositive+FalsePositive}} \qquad (28)$$

$$\boldsymbol{Recall} = \frac{\boldsymbol{TruePositive}}{\boldsymbol{TruePositive+FalseNegative}} \qquad (29)$$

$$\boldsymbol{F-Measure} = \frac{(\boldsymbol{1+\beta^2}) * \boldsymbol{Precision} * \boldsymbol{Recall}}{\boldsymbol{\beta} * (\boldsymbol{Precision+Recall})} \qquad (30)$$

The prediction accuracy is calculated by using the equation (31) that considers the number of records predicted successfully and the total number of records available.

PredictionAccuracy

$$= \frac{\textbf{Number of records predicted successfully}}{\textbf{Total number of records available}}$$

(31)

The overall performance of the proposed disease prediction model is finalized according to the prediction accuracy.

5.2. Experimental Results

In this section, the performance of the disease prediction model is demonstrated in relation to the various contributions of this work. First, the performance of the proposed model is summarised. In this case, 6 useful features were identified and chosen from the heart dataset, which has 15 features in total in the UCI Machine Learning Repository. The necessary features have been selected from the Alzheimer's dataset by using the proposed feature selection and optimization method. The proposed feature selection and optimization method is much faster than existing feature selection algorithms.

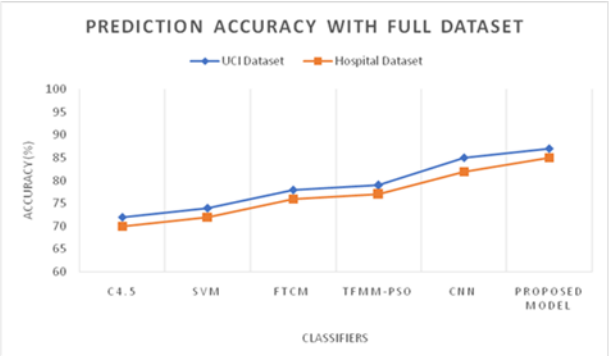

Figure 2. Prediction Accuracy with Full Datasets

The chosen features will be fed into the proposed classification algorithm, which will perform effective classification. The proposed prediction model's performance is evaluated and compared to that of existing classifiers such as C4.5, SVM, FTCM, TFMM-PSO, and CNN. The proposed model includes a deep learning method known as DBN. As a result, the proposed model is also compared to the standard CNN to demonstrate its effectiveness.

Figure 2 depicts the overall disease prediction accuracy on various disease datasets such as the standard diabetic dataset and hospital dataset.

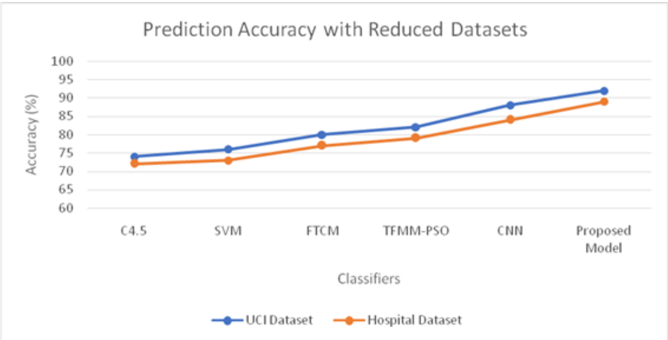

Figure 3. Prediction Accuracy over the reduced datasets

Figure 3 shows that the proposed disease prediction model's effectiveness is demonstrated by comparing it to existing classifiers such as C4.5, SVM, FTCM, TFMM-PSO, and CNN based on disease prediction accuracy on reduced datasets. Even when considering the selected features contained within datasets, the model achieved higher detection accuracy when compared to existing systems.

Table 1 shows the comparative study in terms of prediction accuracy of the newly proposed disease prediction model on full-featured datasets and selected features contained datasets.

Table 1. Comparative Analysis

Disease Datasets	Prediction Accuracy (%)	
	Full features Dataset	Selected Features Contained Dataset
Diabetic Type-1 Disease Dataset	88.2	92.4
Diabetic Type-2 Disease Dataset	87.3	89.8

The work includes a comparative analysis of prediction accuracy, which is shown in table 1. The two standard disease datasets, such as the UCI Diabetic dataset and the Hospital dataset, are considered in two forms here. The selected features contained datasets, and the full features contained datasets.

Table 2 shows the time required for analysis of two different datasets, such as the UCI Diabetic dataset and the Hospital Diabetic dataset. For each dataset, the time required to complete the training and testing processes is considered.

Table 2. Time Analysis

Disease Datasets	Proposed Model		Fuzzy Temporal Cognitive Map	
	Training Time (sec)	Testing Time (sec)	Time taken for Training (sec)	Time taken for Testing (sec)
UCI Diabetic Dataset	0.35	0.18	0.44	0.22
Hospital Diabetic Dataset	1.68	0.77	1.81	0.88

Table 2 demonstrates the efficiency of the proposed disease prediction model in terms of training and testing process time on these two different disease datasets when compared to the existing classification algorithm known as Fuzzy Temporal Cognitive Map, which incorporates fuzzy temporal rules into the decision-making process.

Figure 4 depicts a prediction accuracy comparison of the proposed disease prediction model and domain experts' prediction accuracy. Domain experts are capable of predicting diabetes diseases and categorizing them as type-1 and type-2 levels. This analysis takes into account the following patient record counts: 100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200, 1300, 1400, 1500, and 1600.

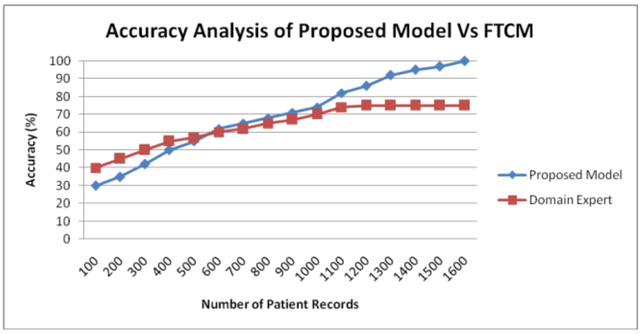

Figure 4. Disease Prediction Accuracy analysis

Figure 4 show that the proposed disease prediction model's disease prediction analysis outperforms the domain expert's prediction accuracy when using the same set of records for the experiments. From the tenth experiment onward, the prediction accuracy on various datasets is nearly equal. The results of the last seven experiments have been reduced and stabilized for the two different the use of fuzzy logic and effective feature optimization is responsible for the newly proposed disease prediction model's efficiency.

The standard evaluation parameters such as precision, recall, and f-measure are taken into account in this analysis, which is shown in table 3 for all two different medical datasets, such as the standard benchmark diabetic dataset and hospital dataset.

Table 3. Performance Analysis

Disease Datasets	Evaluation Parameters		
	Precision Value (%)	Recall Value (%)	F-Measure Value (%)
Standard Diabetic Dataset	92.12	99.35	97.87
Hospital Diabetic Dataset	89.32	99.49	95.58

Table 3 proves the effectiveness of the proposed disease prediction model that incorporates the feature selection method with learning automata and fireworks algorithm and the BSO aware classification algorithm according to the evaluation parameters such as precision, recall, and f-measure. The reason for achieving the highest prediction accuracy is the use of effective BSO and learning automata.

Figure 6 demonstrates the prediction accuracy analysis between the proposed disease prediction model and the existing neural network classifiers such as Back propagation Neural Network (BP), Fuzzy Cognitive Network (FCM), Fuzzy Temporal Cognitive Map (FTCM), Temporal Fuzzy Min-Max Neural Network (TFMM-NN) with Particle Swarm Optimization (TFMM-PSO) (Ganapathy et al 2014) and Convolutional Neural Network (CNN). Here, ten different experiments have been conducted by considering the 10 different sizes with 100, 200, 300, 400, 500, 600, 700, 800, 900, and 1000 records.

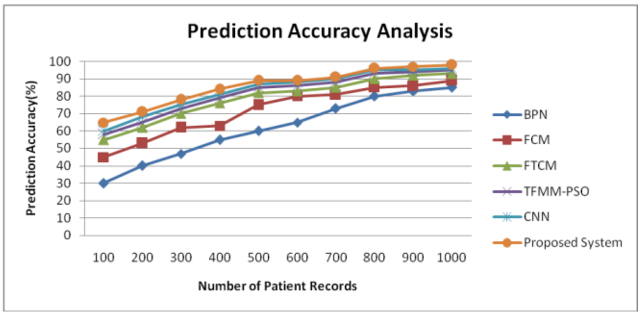

Figure 5. Prediction Accuracy Analysis

Figure 5 demonstrates the disease prediction model's efficiency with the highest accuracy, which is higher than the existing neural network-based classification algorithms such as BPN, FCM, FTCM, TFMM-PSO, and CNN? The reason for the improved results is the use of an effective feature selection process using BSO and learning automata and an effective evolutionary classifier.

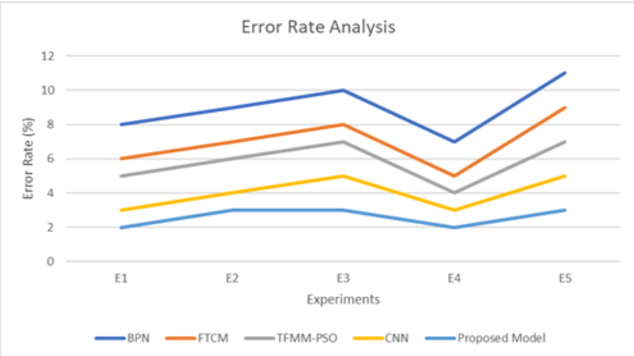

Figure 6. Error Rate Analysis

Figure 6 compares the proposed model to existing neural classifiers such as BPN, FTCM, TFMM-PSO, and CNN in terms of error rate (misclassification rate). Five experiments were carried out, each with a different number of patient records.

Figure 6 show that the newly developed disease prediction model outperforms the existing models that are available as assistance systems for physicians. The performance is due to the incorporation of BSO, Learning Automata, and Temporal Feature Classifier.

6. CONCLUSION AND FUTURE WORK

This work proposes an evolutionary classification model for obtaining required prediction accuracy according to the current requirements, and it is better than the existing classifiers. In this work, an Enhanced Learning Automata based Fireworks Algorithm (ELAFWA) is proposed for performing effective feature selection. Moreover, a new dynamic brain-storming classification algorithm incorporating the Enhanced Fireworks Algorithm (DBSOFA) is also proposed for performing effective classification with optimization. The proposed model is capable of categorizing diabetes patients as having Type-1 or Type-2 diabetes. Furthermore, it warns patients when they are transitioning from type 1 to type 2 diabetes. Finally, the proposed model is proved to be as efficient and effective as the existing disease prediction models. This work can be enhanced further by the introduction of a new deep classifier to achieve better prediction accuracy than this work.

References

1. S. S. Sarmah, "An Efficient IoT-Based Patient Monitoring and Heart Disease Prediction System Using Deep Learning Modified Neural Network," in IEEE Access, vol. 8, pp. 135784-135797, 2020.
2. Y. Pan, M. Fu, B. Cheng, X. Tao and J. Guo, "Enhanced Deep Learning Assisted Convolutional Neural Network for Heart Disease Prediction on the Internet of Medical Things Platform," in IEEE Access, vol. 8, pp. 189503-189512, 2020.
3. M. A. Khan, "An IoT Framework for Heart Disease Prediction Based on MDCNN Classifier," in IEEE Access, vol. 8, pp. 34717-34727, 2020, .
4. Garg, D. K. . (2022). Understanding the Purpose of Object Detection, Models to Detect Objects, Application Use and Benefits. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 01–04. https://doi.org/10.17762/ijfrcsce.v8i2.2066
5. G. S. Bhat, N.Shankar, D.Kim, D.J.Song et al., "Machine Learning-Based Asthma Risk Prediction Using IoT and Smartphone Applications," in IEEE Access, vol. 9, pp. 118708-118715, 2021.
6. P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty and E. Kougianos, "Smart-Log: A Deep-Learning Based Automated Nutrition Monitoring System in the IoT," in IEEE Transactions on Consumer Electronics, vol. 64, no. 3, pp. 390-398, Aug. 2018.
7. W. N. Ismail, M. M. Hassan, H. A. Alsalamah and G. Fortino, "CNN-Based Health Model for Regular Health Factors Analysis in Internet-of-Medical Things Environment," in IEEE Access, vol. 8, pp. 52541-52549, 2020.
8. K. Pothuganti, B. Sridevi and P. Seshabattar, "IoT and Deep Learning based Smart Greenhouse Disease Prediction," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), 2021, pp. 793-799.
9. P. Bide and A. Padalkar, "Survey on Diabetes Mellitus and incorporation of Big data, Machine Learning and IoT to mitigate it," 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 1-10.
10. Romany F.Mansour, José Escorcia-Gutierrez, Margarita Gamarra, Deepak Gupta, Oscar Castillo, Sachin Kumar, "Unsupervised Deep Learning based Variational Autoencoder Model for COVID-19 Diagnosis and Classification", Pattern Recognition Letters, Vol.151, pp. 267-274, 2021.
11. Forum Desai, Deepraj Chowdhury, Rupinder Kaur, Marloes Peeters et al., "HealthCloud: A system for monitoring health status of heart patients using machine learning and cloud computing", Internet of Things, Volume 17, March 2022, No. 100485, pp.
12. Lakshmana prabu S.K., Sachi Nandan Mohanty, Sheeba Rani S.,Sujatha Krishnamoorthy et al., "Online clinical decision support system using optimal deep neural networks", Applied Soft Computing, Vol.81, No.105487, 2019.

13. Lin Liu, Shenghui Zhao, Haibao Chen, Aiguo Wang, "A new machine learning method for identifying Alzheimer's disease", Simulation Modelling Practice and Theory, Vol.99, No.102023, pp. , 2020.
14. Mohsin Raza, M. Awais, W. Ellahi, N. Aslam, Huan X. Nguyen, H. Le-Minh, "Diagnosis and monitoring of Alzheimer's patients using classical and deep learning techniques", Expert Syst. Appl., Vol.136, pp. 353-364, 2019.
15. Tarik Al-Ani, Yskandar Hamam, Redouane Fodil, Frédéric Lofaso, Daniel Isabey, "Using hidden Markov models for sleep disordered breathing identification", Simul. Modell. Pract. Theory, 12 (2004), pp. 117-128.
16. Dongxiao Gu, Jingjing Li, Xingguo Li, Changyong Liang, "Visualizing the knowledge structure and evolution of big data research in healthcare informatics", International Journal of Medical Informatics, Vol.98, pp.22-32, 2017.
17. Simeon Spasov, Luca Passamonti, Andrea Duggento, "A parameter-efficient deep learning approach to predict conversion from mild cognitive impairment to Alzheimer's disease", NeuroImage, Vol.189, pp. 276-287, 2019.
18. Han Wu, Shengqi Yang, Zhangqin Huang, Jian He, Xiaoyi Wang, "Type 2 diabetes mellitus prediction model based on data mining", Informatics in Medicine Unlocked, Vol.10, pp. 100-107, 2018.
19. Ali Kalantari, Amirrudin Kamsin, Shahaboddin Shamshirband,Abdullah Gani, Hamid Alinejad-Rokny, Anthony T.Chronopoulos, "Computational intelligence approaches for classification of medical data: State-of-the-art, future challenges and research directions", Neurocomputing, Vol.276, pp.2-22, 2018.
20. Hamidreza Bolhasani, Maryam Mohseni, Amir Masoud Rahmani, "Deep learning applications for IoT in health care: A systematic review", Informatics in Medicine Unlocked, Vol.23, 2021, 100550.
21. Kohzoh Yoshino, Ayano Kawaguchi, Shogo Yata, Akinori Iyama, Saburo Sakoda, "Analysis of heart rate response to obstructive apnea/hypopnea events in patients with Parkinson's disease with relatively severe sleep apnea syndrome", Informatics in Medicine Unlocked, Vol. 23, 2021, 100554.
22. Bhushankumar Nemade, Deven Shah, "An efficient IoT based prediction system for classification of water using novel adaptive incremental learning framework", Journal of King Saud University - Computer and Information Sciences, Available online 28 January 2022.
23. Garg, D. K. . (2022). Understanding the Purpose of Object Detection, Models to Detect Objects, Application Use and Benefits. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 01–04. https://doi.org/10.17762/ijfrcsce.v8i2.2066
24. V.Nanda Gopal, Fadi Al-Turjman, R.Kumar, L.Anand, M.Rajesh, "Feature selection and classification in breast cancer prediction using IoT and machine learning", Measurement, Vol. 178, No.109442, 2021.
25. Shreshth Tuli, Nipam Basumatary, Sukhpal Singh Gill, Mohsen Kahani, Rajesh Chand Arya, Gurpreet Singh Wander, Rajkumar Buyya, "HealthFog: An ensemble deep learning based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in integrated IoT and fog computing environments", Future Generation Computer Systems, Vol.104, pp. 187-200, 2020.
26. Garg, D. K. . (2022). Understanding the Purpose of Object Detection, Models to Detect Objects, Application Use and Benefits. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 01–04. https://doi.org/10.17762/ijfrcsce.v8i2.2066
27. Mohammed Farsi, "Application of ensemble RNN deep neural network to the fall detection through IoT environment", Alexandria Engineering Journal, Vol.60, No.1, pp.199-211, 2021.
28. Yuxin Zhou, Yinan Lu, Zhili Pei, "Intelligent diagnosis of Alzheimer's disease based on internet of things monitoring system and deep learning classification method", Microprocessors and Microsystems, Vol.83, No.104007, 2021.
29. Mazin Alshamrani, "IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey", Journal of King Saud University - Computer and Information Sciences, 2021.
30. Farman Ali, Shaker El-Sappagh, S.M. Riazul Islam, et al "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion", Information Fusion, Vol.63, pp. 208-222, 2020.
31. A.V.L.N.Sujith, Guna SekharSajja, V.Mahalakshmi, Shibili Nuhmani, B.Prasanalakshmi, "Systematic review of smart health monitoring using deep learning and Artificial intelligence", Neuroscience Informatics, Vol.2, No.3, 2022.
32. S.Ganapathy, K.Kulothungan, S.Muthurajkumar, M.Vijayalakshmi, P.Yogesh, A.Kannan, "Intelligent feature selection and classification techniques for intrusion detection in networks: a survey", EURASIP Journal on Wireless Communications and Networking, Springer, Vol. 271, No.1, pp. 1-16, 2013**.**
33. Garg, D. K. . (2022). Understanding the Purpose of Object Detection, Models to Detect Objects, Application Use and Benefits. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 01–04. https://doi.org/10.17762/ijfrcsce.v8i2.2066
34. S Ganapathy, R Sethukkarasi, P Yogesh, P Vijayakumar, A Kannan, "An intelligent temporal pattern classification system using fuzzy temporal rules and particle swarm optimization", Sadhana, Springer, Vol. 39, No.2, pp. 283-302, 2014.
35. R Sethukkarasi, S. Ganapathy, P Yogesh, A.Kannan, "An intelligent neuro fuzzy temporal knowledge representation model for mining temporal patterns", Journal of Intelligent & Fuzzy Systems, IOS Press, Vol. 26, No.3, pp. 1167-1178, 2014.
36. U Kanimozhi, S Ganapathy, D Manjula, A Kannan, "An Intelligent Risk Prediction System for Breast Cancer Using Fuzzy Temporal Rules", National

Academy Science Letters, Vol. 42, No. 03, pp. 227-232, 2019.
37. M. Raza, M. Awais, W. Ellahi, N. Aslamd, H.X. Nguyen, H. Le-Minh, "Diagnosis and monitoring of Alzheimer’s patients using classical and deep learning techniques", Expert Systems With Applications, Vol.136, pp. 353-364, 2019.
38. Lin Liu, Shenghui Zhao, Haibao Chen, Aiuo Wang, "A New Machine learning Method for Identifying Alzheimer's Disease", Simulation Modelling Practice and Theory, Vol.99, No.102023, pp. 1-12, 2020.
39. Yuxin Zhou, Yinan Lu, Zhili Pei, "Intelligent diagnosis of Alzheimer's disease based on internet of things monitoring system and deep learning classification method", Microprocessors and Microsystems, Vol.83, No.104007, 2021.
40. Shuangshuang Gao, "Gray level co-occurrence matrix and extreme learning machine for Alzheimer’s disease diagnosis", International Journal of Cognitive Computing in Engineering, Vol.2, pp. 116-129, 2021.
41. Cermakova P, Eriksdotter M, Lund LH, Winblad B, Religa P, Religa D, "Heart failure and Alzheimer's disease, Journal of Internal Medicine, Vol.277, pp. 406–425, 2015.
42. Muhammad Shahbaz, Shahzad Ali, Aziz Guergachi, Aneeta Niazi, Amina Umer, "Classification of Alzheimers Disease using Machine Learning Techniques", In Proceedings of the 8th International Conference on Data Science, Technology and Applications (DATA 2019), pp. 296-303, 2019.
43. Expert Committee on the Diagnosis and Classification of Diabetes Mellitus. Report of the expert committee on the diagnosis and classification of diabetes mellitus. Diabetes Care 26:S5-S20; 2003. [PubMed]
44. Chawla, A. (2022). Phishing website analysis and detection using Machine Learning. International Journal of Intelligent Systems and Applications in Engineering, 10(1), 10–16. https://doi.org/10.18201/ijisae.2022.262
45. Garg, D. K. . (2022). Understanding the Purpose of Object Detection, Models to Detect Objects, Application Use and Benefits. International Journal on Future Revolution in Computer Science &Amp; Communication Engineering, 8(2), 01–04. https://doi.org/10.17762/ijfrcsce.v8i2.2066
46. Junqi Zhang, Lei Che, Jiang Chen, "Learning Automata-based Fireworks Algorithm on Adaptive Assigning Sparks",LNCS, Vol.12145, pp. 59-70, 2020.
47. Tan, Y., Zhu, Y.: Fireworks algorithm for optimization. In: Proceedings of theInternational Conference on Swarm Intelligence, Beijing, China, pp. 355–364, June2010.
48. Zheng, S., Janecek, A., Tan, Y.: Enhanced fireworks algorithm. In: IEEE Congresson Evolutionary Computation (CEC), pp. 2069–2077, June 2013.
49. Zheng, S., Janecek, A., Li, J., Tan, Y.: Dynamic search in fireworks algorithm. In:IEEE Congress on Evolutionary Computation (CEC), pp. 3222–3229, July 2014.
50. Narendra, K.S., Thathachar, M.A.L.: Learning automata - a survey. IEEE Trans.Syst. Man Cybern. SMC–4(4), 323–334, 1974.