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Predicting Microvascular Complications in Diabetic Mellitus Using Improved Enhanced Coati Optimizer

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Abstract: Diabetes complications are classified as Macro and Microvascular Diseases. Microvascular complications in type 2 Diabetic patients commonly occur as diabetic retinopathy, diabetic neuropathy, and diabetic nephropathy. Therefore detecting these microvascular complications from the clinical dataset is very important. The paper proposed a machine learning model for predicting and detecting microvascular diseases in type 2 diabetic Patients. In the initial stage data preprocessing is performed upon data. After the preprocessing feature selection is done using the Improved Enhanced Coati algorithm. The optimal features from the Improved Enhanced Coati Optimization algorithm are applied to various classification algorithms. The results are obtained for traditional classifiers such as XGB, KNN, SVM, RF, AdaBoost, Tree, and ANN algorithms. For the classification of diabetic retinopathy, the selected features are age, sex, BMI, BP, FPS, Family History, and Medical Adherence. Similarly, the features used to classify Diabetic Nephropathy are Sex, SP, FPS, Family History, Onset Age, and HbA1C and FPS used to classify Diabetic Neuropathy. On optimal selection of features various ML classification algorithms are applied. The results are compared with XGB, KNN, SVM, RF, AdaBoost, Tree, and ANN. The results are measured for training and testing on parameter accuracy and Random Forest Classifier results are optimal for the AdaBoost estimator for type 2 diabetic patients for the diabetic retinopathy is 99.9% and 94.78%, diabetic nephropathy, diabetic neuropathy is 99.8% and 95.44%. In the proposed methodology the feature-selecting fitness function is selected based on the received optimal accuracy from the feature-selecting estimator as AdaBoost. In Coati Optimizer the feature selection process is done by a fitness function that provides the minimum error.

Keywords: Enhanced Coati Optimizer, Feature Selection, Microvascular Complications, Machine learning classification algorithms, Bio-inspired algorithms

1. INTRODUCTION

Diabetes is a long-term condition that continues to be an expanding and international concern as it affects the health of all people worldwide. It is a common disease caused by a metabolic condition that causes elevated glucose levels. Basically, in type 2 diabetes the pancreas makes insulin but cells are inefficient to resist as they should. Hence glucose can't get into cells and raises the blood sugar level [1]. This long-term prevalence of diabetes affects human organs and is responsible for microvascular and macrovascular complications in patients. Due to macro and microvascular complications in type 2 diabetic patients various health issues may occur. Hence the understanding of the count of the diabetic patient is very essential. As per the IDF Diabetes Atlas 10th edition, in the age group 20-79 overall world the diabetic patent count is predicted to be 643

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million by 2030. And the specified count of mortality due to diabetic complications is 6.7 million which is a serious issue [2]. The possible complications in diabetic type 2 patients are categorized into macro and microvascular complications. These complications occur due to the long-term presence of diabetes in type 2 patients [3].

Macrovascular challenges originate from damage in the enormous blood arteries of the circulatory system, brain, and legs [4]. This causes chronic coronary artery disease, peripheral arterial disease, and neurological illness [3]. Similarly, in diabetic patients, if the complication affects the small blood arteries in organs such as the retina, kidney, or nerves, it creates microvascular complications such as diabetic retinopathy, nephropathy, and neuropathy [5]. These diabetic complications leading impact morbidity and mortality. The paper focuses on microvascular diabetic complications commonly occurring in type 2 patients. Therefore early prediction of diabetic retinopathy, diabetic nephropathy, and diabetic neuropathy is very essential. For this medicinal practitioners regularly conduct the health checkup. In that checkup process patients need to appear for specified clinical tests. Nowadays this data is stored in the form of digital forms called medical records of the patients, hospital records, and clinical reports of the patients. Doctors and researchers use digital health records to analyze large amounts of patient data to identify trends and improve healthcare. On doctors' experience and knowledge, diagnosis is done which can be inaccurate as it's a manual decision. In some cases, unnoticed hidden patterns affect the decision-making of doctors. Therefore machine learning algorithms help doctors to understand the hidden patterns and help in making decisions accurately [6], [7].

The clinical parameters analyzed for predicting diabetic microvascular complications are the duration of diabetes, age, sex, Hb1AC, Blood pressure, Eating habits, stress, family History, etc. Due to these factors, it is easy to predict the probable occurring complications in patients using machine learning systems. Data-driven approaches utilizing supervised machine learning techniques for identifying patients with these conditions. Several researchers have attempted to develop a precise diabetes model for prediction over the years. However, this area still faces substantial open research challenges due to a lack of relevant knowledge sets and prediction tools, pushing researchers to use analytics- and machine learning (ML)-based methodologies. Using machine learning models are inquired to solve problems and examine healthcare prediction analytics [8]. Machine learning perdition algorithms have been developing and reliable in recent years. These algorithms are used to preprocess and select relevant features from the datasets and automate the prediction. Machine learning models allow us to identify the risk of microvascular and microvascular complications [9]. Statistical tests are ANOVA, and descriptive analysis techniques are used to predict diabetic complications [10].ML predictive models use the standard deviation and mean for the performance tree, and for validation use c-statistics [11]. These Machine learning techniques significantly influence the model performance and shape new horizons for prediction, and outcome definition [11].

The paper discusses a novel approach suggested for the feature selection technique in microvascular complications. Later these optimal features are provided to the various classification algorithms and results are measured on various measuring parameters.

2. LITERATURE SURVEY

Various research uses the machine learning algorithm for predicting complications in the healthcare sectors. The researcher developed various learning models for predicting the risk of diseases. In type 2 diabetic patients various researchers are developing machine learning models for predicting diabetic retinopathy, diabetic neuropathy, and diabetic nephropathy. Related work concerning microvascular complications is discussed in this section.

Sarah Kanbour et al discussed machine learning models for predicting diabetic retinopathy, diabetic kidney, and diabetic neuropathy in type 2 diabetic patients. These microvascular complications are predicted from 256 features [11].

Cichosz et al suggested the predictive model for long-term chronic diseases caused due to diabetes based on the predictive models. Therefore the model is based upon the data pattern as a multiple logistic model which can find the dependent complications based on the independent parameter [12].

Dagliati et al proposed a data mining and predictive model for the type 2 microvascular complication prediction model with center profiling for assessing the features and predictive model constructed using RF imputation algorithm as miss Forest. RF imputation uses 100 trees and a maximum of 100 iterations using RMSE and RMSEN on missing values. To validate the results, the Leave-one-out strategy is used [13]. The prevalence of microvascular complications is predicted using log-binomial and Poisson regression. The model suggests prevalence due to different pathophysiological mechanisms [14].

Vamsi et al proposed a machine learning model RF with a Decision tree that provides the optimal results for classifying microvascular and macrovascular complications. The network for diabetic complications identifies the relationship between the patients and the common health complications [15].

In Smart Framework researchers suggested a machine learning model to predict the prevalence of. Microvascular diseases in patients based on the decision theory. In a smart framework, the prediction parameters are auto-stunned hence the uncertainty and Errors are in the selection model. The decision theory consists of three elements plausible features, alternative decisions, and objectives. The uncertainties are associated with the decision-making using the likelihood prediction technique for classifying multiple replications. Hence this framework works upon data-driven model selection [16].

Nicolucci A. et al, suggested a supervised machine learning model as XGBoost for predicting six groups of diabetic complications retinopathy, neuropathy, nephropathy, cardiovascular diseases, cerebrovascular, and peripheral vascular disease. This model helps in finding the greater risk of diabetic complications using XGBoost. This improves the quality of diabetic care [17].

The researchers Branimir L et al, suggested RNN LSTM and RNN GRU are designed to predict microvascular complications and results are compared with random forest and multilayer perceptron for diagnosing and designing are compared with the random forest and multiple perceptions [18].

The risk engine suggested by Hui Shao et al is an analytical tool that collects a large amount of the population which allows the simulation to indicate the progression of diabetes using the BRAVO model using the ACCORD trial database to predict the complications due to diabetes [19].

Weiss et al suggested a machine learning model for predicting microvascular complications from electronic health data by calculating risk scores. Risk calculation using a regularized Cox model and wavelet reconstruction network. The c-statistics test is used to predict the risk of microvascular complications [20].

Rashid et al used demographic, clinical, and laboratory datasets for predicting microvascular complications. To select features the chi-square test is used. After selecting features from the chi-square test these features are applied to various machine learning models and compared performance.The diagnosed complications as CAN, DPN, NEP, and RET [21].

Dagliati et al have suggested a data-mining pipelined model comprising 5 stages central profiling, prediction model targeting, predicting model construction, and model validation. The central profiling stage focuses on derivative prediction. For the second stage of pipelining predictive model construction works on the dataset collected from the physician and set threshold values for microvascular complications as 3,5, and 7 years. In predictive model construction data imputation is performed using mean, mode, median, and miss forest. Prediction model validation uses LOO, Sensitivity, specificity, accuracy, PPV, NPV and ROC, and MCC [13].

Vamsi et al designed a classification model for micro and macrovascular disease prediction. The data preprocessing step executes by deleting rows and columns where more than 70% of data is missing. Feature selection is performed using a chi-square test and applied to a machine-learning model where a random forest with a decision tree provides more accuracy [15].

XGBoost algorithm is used to classify diabetic complications as micro and macrovascular diseases. The work predicts the probability of any micro and macrovascular complications in type 2 diabetic patients throughout 3, or 5 years and model evaluation uses performance measures such as ROC and AUC [22].

Missing values are calculated using various classifiers and the count for the missing values is more than 60%. Hence, data imputation uses three approaches replacing missing values using mean, k-NN model, and missForest. Later RMSE was calculated for the dataset and missForest results are more reasonable. Balancing of the dataset is carried out by using SMOTE analysis. The feature selection process is carried out using Logistic Regression and SVM linear classifier and classification results are best for RF, AdaBoost, and XGBoost classifiers [23].

Haque et al used LMAV and NSV methods for feature extraction for EMG in the time domain.GRF feature extraction is carried out using Discrete Wavelet decomposition. Feature selection is performed using the chi-squared test. PCA is used for dimensionality reduction purposes. Later machine learning algorithms such as DAC, ECM, KCM, KNN, LCM, NBC, SVM, and BDC classification algorithms are used [22].

Jelinek et al, suggested automated detection of diabetic neuropathy using machine learning. ECG signals are applied to multi-scale Allen factors to determine heart rate variability. This uses a based learning system for diagnosis purposes [24].

The proposed system harnesses a Chebyshev Filter during pre-processing, chosen for its efficacy in swiftly transitioning between frequencies while maintaining tolerable ripple in image processing applications. It excels effectively in edge detection and noise elimination, efficient for enhancing image quality and clarity. Moving forward, feature extraction is accomplished through Mel-frequency cepstral coefficients (MFCC), renowned for compressing high-frequency information within a nonlinear scale. This compression renders MFCC robust against noise interference and less prone to variations in speech patterns induced by background noise, ensuring reliable feature extraction in diverse environmental conditions. Subsequently, the extracted features undergo clustering using the K-means algorithm, facilitating the identification of distinct patterns within the dataset. This step aids in organizing the data for subsequent classification. For classification purposes, the Support Vector Machine (SVM) algorithm is employed, known for its proficiency in discerning complex patterns and effectively categorizing data points. Lastly, to interpret emotional cues embedded within the data, an Adaptive Generative Algorithm is deployed. This sophisticated approach adapts dynamically to the nuances of emotional expression, enabling accurate interpretation and classification of emotional states. By integrating these advanced techniques, the proposed system offers a comprehensive framework for processing and analyzing data, particularly suited for tasks requiring a nuanced understanding of both visual and emotional information [25].

In the initial stages of data processing, the proposed system employs the min-max scalar technique for data pre-processing. This method scales the features in a dataset to a specified range, enhancing the consistency and comparability of the data across different variables. Following pre-processing, Principal Component Analysis (PCA) is applied for feature extraction from the images. PCA, a widely used dimensionality reduction technique, identifies the most significant patterns in the data by projecting them onto a lower-dimensional space while retaining as much variance as possible. By reducing the dimensionality of the feature space, PCA simplifies the subsequent classification process while preserving the essential information necessary for accurate analysis. For classification, the system adopts a Multinomial Bayesian Ordinal Probit Regression model. This model excels in handling multi-class classification tasks, leveraging Bayesian principles to estimate the probability distributions of class labels. By incorporating ordinal probit regression, which models the ordinal relationships between classes, the system can accommodate complex classification scenarios where the classes possess a natural order or hierarchy. By integrating these techniques, the proposed system offers a robust framework for data analysis and classification, capable of handling diverse datasets and extracting meaningful insights with high accuracy [26].

In medical diagnostics, the proposed system introduces a Convolutional Neural Network (CNN) architecture tailored specifically for disease diagnosis. To ensure the reliability and accuracy of the model, a validation step is integrated, wherein a Mildly Fine-tuned VGG16 model is preloaded with weights from ImageNet. This fine-tuning process optimizes the VGG16 architecture for the specific task of medical image analysis, enhancing its performance and adaptability to medical datasets. For binary classification tasks involving chest X-ray images, the system recommends CovCXR-Net, a specialized CNN model optimized for this purpose. Additionally, for multi-class classification, a Single Deep Network is suggested. Specifically, MDCXR2-Net is employed for classifying three diseases, while MIDCXR4-Net is utilized for classifying four diseases. These models are tailored to handle the complexities inherent in medical image analysis, leveraging deep learning techniques to extract meaningful features and accurately classify diseases based on visual cues in the images. By utilizing these advanced CNN architectures, the proposed system offers a powerful tool for disease diagnosis, capable of achieving high accuracy and reliability in medical imaging tasks [27].

In the implemented feedback architecture, the BFGS Quasi-Newton training algorithm (trainbfg) played a pivotal role in a comprehensive analysis of solutions in derivation using the mathematical model underlying the given problem. This sophisticated algorithm enabled the iterative refinement of model parameters by efficiently updating the inverse Hessian matrix approximation. By leveraging the curvature information of the objective function, BFGS facilitated rapid convergence towards optimal solutions while mitigating the computational burden associated with exact Hessian computation. Through this iterative optimization process, the feedback architecture systematically evaluated the performance and efficacy of the mathematical model in addressing the problem at hand. By scrutinizing the solutions obtained through this methodology, the system could identify potential areas for improvement, refine model parameters, and enhance overall predictive accuracy. Integrating BFGS within the feedback architecture provided a robust framework for analyzing and optimizing the mathematical model, ensuring its effectiveness in tackling real-world challenges [28].

Microvascular disease in type 2 diabetic patients is detected using the White Shark Based Extreme Gradient Boost method. This method is used for classifying diabetic retinopathy, neuropathy, and nephropathy [29].

Table I illustrates the feature selection algorithms employed by diverse researchers for diagnosing or predicting microvascular complications in type 2 diabetic patients. This critical aspect of research methodology involves identifying the most informative and relevant features from complex datasets, enabling accurate classification or prediction of diabetic complications. By selecting the optimal features, researchers can enhance the efficacy of their diagnostic or predictive models, ultimately contributing to improved patient outcomes and healthcare decision-making. Effective feature selection algorithms are paramount in uncovering meaningful patterns and relationships within diabetic data, facilitating early detection and targeted interventions for microvascular complications.

Feature selection is selecting feature subsets from the available features based on certain selection criteria. Generally, bio-inspired algorithms are inspired by physical properties. These selection algorithms are used for dimension reduction. These algorithms are Genetic algorithms, Evolutionary Strategies, and Differential Evolution. Swarm Intelligence is an emerging paradigm that uses adaptive systems based on a genetic adaptation of organisms and the social behavior of organisms. Some suggested feature selection algorithms are Artificial Bee Colony Algorithm, Ant colony, Fish Swarm Algorithm, Artificial Immune system algorithm, Firefly algorithm, Group Search optimizer, Shuffled Frog Leaping Algorithm, PS20, Intelligent Water Drops algorithm, and many more [30]. These algorithms are discussed below:

A. Particle Swarm Optimization:

A population-based algorithm modeled by the social movements of birds or fish schools. Birds' social behavior is

TABLE I. FEATURE SELECTION ALGORITHMS FOR MICROVASCULAR COMPLICATION PREDICTION.

Author	Feature selection algorithm	Diagnosed Microvascular complication
Rashid et al [21]	Chi-square test	CAN, DPN, NEP, and RET.
Dagliati et al [13]	RF Approach	Nephropathy, neuropathy,retinopathy.
Vamsi et al [15]	Chi-square test	NEP, NEU, RET, CVD, PVD.
Jian et al [23]	LR and Linear SVM	Metabolic Syndrome, dyslipidemia, NEP, NEU, diabetic foot, hypertension, obesity, RET.
Haque et al [22]	Chi-squared	Diabetic Neuropathy
Jelinek et al [24]	Multi-scale Allen Factor	Diabetic Neuropathy

to flock or roost. The individual particles iteratively modify the entire solution. Each particle searches the space with an identifiable velocity in the same direction and has its impact by its own best location found so far, the best solution, and the global solution [31].

B. Ant colony algorithm:

This algorithm is inspired by the Ant. The solutions are improved through local search in the local search phase and finally updated in update pheromones [32], [33]. Ant Colony Optimization uses two approaches pheromone and decision making. The pheromone variable is associated with each edge and can be read and updated by ants. The pheromone value is correlated with the solution component. In ACO optimization successful variants are the MAX-MIN ant system and Ant colony system [34].

C. Glow-worm Swarm Optimization :

This algorithm suggests multiple optima of multimodal function which makes it different from the PSO and ABC algorithms. This calculates the fitness of the current location and accordingly calculates the objective function into luciferin value that is broadcasted to neighbors. Identification of neighbor and movement computation exploited using adaptive neighborhood by sensor range. This algorithm solves the issue by locating a global optimum solution for instances that suffer due to the low accuracy, local optimum, convergence of success rate, and reduced speed [35].

D. Artificial Bee Colony Algorithm:

The Artificial Bee Colony Algorithm is based on the particular intelligent behavior of the honeybee. In this algorithm, three groups of bees exist employed bees, onlookers, and scouts. The employed bee and onlookers bees search the food and scout group present at the hive. This algorithm converts the problem of finding to best parameter which minimizes an objective function [36].

E. Zebra Optimization Algorithms:

The name suggests that algorithm is inspired by the Zebra. The performance of the algorithm is evaluated on 68 benchmark functions. These functions are unimodal, high, fixed dimensional multimodal, according to Congress on Evolutionary Computation Standards 2015 and 2017. In ZOA two natural behaviors of Zebras in wild animals are considered foraging and defense strategies against predators. In the foraging phase pioneer zebra is the best member and leads the population towards the search space and in Defence strategies against predator attacks update the position of the population in the search space. In this problem, each zebra is a candidate solution for the problem which searches space for the problem. While considering the predator attack there are two possibilities attack by a lion or other than a lion. In case of a lion attack zebra chooses to escape and for others, it selects to offensive strategy [37].

F. Bacterial Foraging Optimization:

Bacterial foraging is inspired by the theory of foraging means animals search for nutrients and obtain nutrients to maximize energy intake. This uses E.coli bacteria and models chemotaxis, tumbling, and swimming behavior to navigate search space and to find an optimal solution [31].BCF combines chemotaxis with cell-to-cell which improves the speed of bacterial colony. The area concentrates on search and maintains diversity in the search process. BCF models are a self-adaptive foraging strategy that dynamically balances exploration and exploitation behavior and enables information sharing among ant colonies [38].

G. Cuckoo Search Algorithm (CSA):

The Cuckoo Search Algorithm is based on obligated brood parasite habits of several cuckoo species as well as the Levy fight behavior of some birds and fruit flies. Parasitic cuckoos select a nest where the host bird just laid down its eggs which increases the cuckoo's chick's share of food provided by its host bird. The cuckoo search follows three idealized rules as [39], [40]

1) Laying one egg at a time and dumping it to a randomly chosen nest.
2) The best nest for high-quality eggs carries over to the next generation
3) Several available host nests are fixed and the egg laid by the cuckoo is discovered by the host with a probability of 0 or 1.

H. Cuttlefish optimization algorithm:

The method replicates the cuttlefish's color-changing behavior mechanism, it is subsequently used to solve numerical global optimization problems. This algorithm is associated with two processes reflection and visibility.

These processes are achieved by stacking Chromophores, Iridophores, and Leucophores. The Cuttlefish Optimization algorithm initializes the population with random solutions and calculates and keeps the best solution and average values of the best solution point. The interaction among chromatophores and iridophores cells in global search cases produces the reflection and visibility of the entire search space and escapes local optima. The iridophores cell calculates the new solution based on reflected light from the best solution and visibility matches the local search. The leucophores in the Enhanced local search case are responsible for producing a new solution. The leucophores operate in mimic cases and are responsible for a random solution by reflecting incoming light called global search [41].

I. Salp Swarm Algorithm:

The Salp Swarm algorithm has characteristics such as competency, flexibility, and simplicity. SSA is a stochastic algorithm that has a considerable number of random components which improves the performance of the metaheuristic algorithm. In the Salp swarm algorithm population randomly searches the space corresponding to the dimensions of the problem. The leader salp updates the position as per the best objective function value in the current iteration. Leader Salp searches for the optimal solution using mathematical functions by considering the current and random values. As per the leader Salp's position followers, Salp updated their position and position chain and tried to be closer to a better Solution. The objective function values of salps are evaluated after each update. The iteration continuous until the stopping criteria is not met. This stopping criterion is a maximum number of iterations or achieving a desirable level of accuracy [42].

J. Fish Swarm Algorithm:

The Fish Swarm algorithm is a metaheuristic optimization technique inspired by fish schools from the behavior of collective movement and social behaviors. The steps in the fish swarm algorithm are initializing the search space corresponding to the problem dimension. This assigns fitness value to the objective function. In the movement step preying, swarming, and following such steps exist. In the preying stage, the position of fitness value is updated based on the current position. In the swarming stage, it avoids overcrowding and in the following step, fish with lower fitness tend to be close to higher fitness value. Later evaluation of each fitness is carried out using an objective function [43].

K. Intelligent Water Drops Algorithm :

Intelligent water drops algorithm is inspired by the drop of water flowing in the river. This drop of water flows with lots of twists and turns in the river along with its two main properties, velocity and soil. IWD has two parameters are constant during the lifetime as static parameters and another parameter dynamic which reinitializes each iteration. The basic principle of the intelligent water drops algorithm is to populate the ”water drops”.The water drops used in the algorithm are virtual agents in a virtual setting. The ”soil” that each drop of water brings, and each drop represents a possible way to solve the issue at hand. Water droplets represent various options or states in the problem as they flow across a network of nodes. They change the quantity of ”soil” they carry and may even improve their solutions as they travel and interact with the surroundings and other water droplets [44].

L. Chaotic Sinusoidal Map(CSM)-enhanced Zebra Optimization Algorithm:

The Chaotic Sinusoidal Map (CSM)-enhanced Zebra Optimization Algorithm (CZOA) merges chaotic dynamics with optimization algorithms to boost problem-solving capabilities. CZOA utilizes CSM's chaotic behavior to infuse randomness, preventing local optima stagnation. CSM's sensitivity to initial conditions produces diverse, unpredictable trajectories across the search space. Integrated with Zebra Optimization Algorithm (ZOA), CZOA achieves a balanced exploration-exploitation strategy, facilitating efficient global optimization. Inspired by zebra herds, ZOA's population-based approach fosters collaboration and competition among solutions. CZOA's incorporation of CSM injects further randomness, enhancing its ability to escape local optima and discover varied solutions. This fusion of chaotic dynamics and population-based optimization empowers CZOA as a versatile framework for solving intricate optimization challenges, promising effectiveness across diverse domains [45].

These algorithms are used in healthcare for feature selection and classification. The role of Bio-inspired feature selection and classification algorithms is discussed in below:

For feature selection purposes algorithm is cat swarm optimization, kill herd, and bacterial foraging. After selecting optimal features from these to classify the disease uses Support Vector Machine algorithm [46].

Sakri et al used PSO for predicting features. The PSO algorithm can explore optimal solutions as the particle can explore different parts of solution space. This stores the feature selection in the memory and knowledge of solution based on particle fly within the problem space. PSO performance is unaffected by the dimension of the problem. PSO selects best-fit features applied to the classification model [47].

Table II, elucidates the computational complexity associated with Swarm Intelligence Algorithms. This analysis offers insights into the algorithm's efficiency and scalability, crucial for evaluating its feasibility in real-world applications. Understanding computational complexities aids in selecting the most suitable algorithm for diverse problem domains and resource constraints. The researchers provided various models [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63] are lacking due to optimal feature selection. The measure parameters don't provide the optimal

TABLE II. SWARM INTELLIGENCE ALGORITHMS AND COMPUTATIONAL COMPLEXITY.

Sr No	Algorithm	Computational Complexity
1	Ant Colony [33], [48]	O($n^2.2 * m$) where n: number of nodes in the graph m: number of ants in colony.
2	Artificial Bee Colony Algorithm [49]	Initialization O(S*N) where S: Colony Size and N: Number of Variables. Employed Bee Phase: O(S*N) Onlooker Bee Phase: O(S^2)$ScoutBeePhase : O(S)$ Worst Case: O(S*N)*iterations
3	Zebra Optimization Algorithm [37]	Initialization O(N.m) where N: Number of Zebras and m: number of problem variables Update Process Complexity: O(2*N*m*T) Total Computational Complexity: O(N*m*(1+2*T))
4	Bacterial Foraging Optimization [50]	Initialization O(N.m) where N: Number of Zebras and m: number of problem variables Update Process Complexity: O(2*N*m*T) Total Computational Complexity: O(N*m*(1+2*T))

solution for microvascular prediction. Hence the paper suggests a bio-inspired feature selection model Enhanced Coati Optimization model, which selects solutions based on the fitness function. These fitness functions are calculated from global and local solutions. These three feature selection algorithms add three back propagation neural networks.

3. PROPOSED METHODOLOGY

To identify and select the most pertinent and useful features from a dataset, feature selection algorithms significantly contribute to the performance and comprehension of predictive models in the context of healthcare labeling difficulties. Hence the researchers use feature selection as the primary and important step in predicting microvascular complications in diabetic type 2 patients.

Correlation-based feature selection works upon heuristics search strategy by evaluating the appropriate correlation measures. This finds the similarity measures among the two features between the +1 and -1 correlation coefficients [64]. This feature selection techniques are used for various evaluation measures. These evaluation measures are Information theory and consistency-based measures. Correlation-based feature selection selects the highest correlation with the target variable and the lowest correlation with each other.

Genetic algorithms are used for feature selection which selects the best features by simplifying mathematical models [65]. The genetic algorithm solves constrained and unconstrained optimization problems. These genetic algorithms are population-based and heuristic methods that are inspired by man [66]. Genetic algorithms use three important steps selection, reproduction, and termination. In a genetic algorithm, Individuals within the population compete for resources and mates.

Individuals who are successful (fittest) mate to produce more children than others.Genes from the "fittest" parent are passed down across generations, which means that parents may produce offspring that outperform either parent. Thus, each subsequent generation is more matched to their surroundings [67].

To achieve a Pareto front of non-dominated solutions with both low cost and high classification performance, a PSO-based multi-objective feature selection strategy is used for the cost-based situation. We examine HPPSOFS, a multi-objective approach to PSO with hybrid mutation, to reach this objective [68].

Discrete issues with partial information and poor computational power are referred to as optimization difficulties. These difficulties can be overcome using Meta-heuristic algorithms. Meta-heuristic algorithms take into account three elements:

Three factors influence an objective function [69]:

1) it is maximized or minimized;
2) a set of unknowns or variables impacts the objective function
3) a set of restrictions, on which optimization problems are focused, allows the unknown to accept some values and exclude others.

The proposed system is a bio-inspired feature selection model. This is metaheuristic bio-inspired by the attacking and hunting behavior of iguanas called exploration and escape from predators called exploitation [70]. The fitness function selects the optimal features are based on the classification algorithm which provides greater accuracy. Figure 1 shows the workflow of the proposed system. The Enhanced Coati Optimizer [71] finds a robust and efficient algorithm. It uses the balanced exploration and exploitation called Levy flight search, Adaptive learning rate, and information sharing.

The proposed method uses a Feature selection algorithm as Enhanced Coati Optimized. To this, the applied feature estimators' algorithms are KNN, SVM, AdaBoost, and Tree. The optimal results from the estimator are later applied to the Classification algorithm to classify the microvascular disease

In the proposed system, the levy flight search uses the estimator functions as KNN, SVM, AdaBoost, and Tree. These algorithms search the efficient patterns. Later stage apply adaptive learning which adjusts the iterations based upon the selection of the estimators which improves the exploitation. Information sharing among the coatis enhances the collaboration.

The used dataset for the feature selection algorithm is "Micro and Macro Vascular Complications in Type 2 Diabetes". This dataset contains information on type 2 diabetic patients. The input parameters are age, BMI, Systolic BP, Diastolic BP, HbA1c, Family History, Onset age, Smoking, and Medication usage, and categories are diabetic retinopathy, nephropathy and neuropathy [72].

The algorithm for the Improved Enhanced Coati Algorithm is discussed below:

Algorithm: Proposed System

Step 1: Select the data set and divide it for training and testing

Step 2: Apply Feature Estimator for the Enhanced Coati Optimizer

a. Apply estimator as KNN, SVM, AdaBoost, and Tree.

b. Compare the Accuracy of each estimator.

c. Select the Optimal accuracy-providing estimator.

In this algorithm, each coati stores the information about its current position called local solution and fitness quality Global solution. The sharing of the information among each other is carried out during each iteration and hence position storage and fitness value storage is done. While performing these processes in the improved Enhanced Coati algorithm based on the current understanding called local solution the information is carried forward to explore the new promising area. Later the Local solution, current solution, and global solution are compared to refine the Global solution.

These information-sharing probabilities are based on fitness-based sharing which is the better solution and provides the higher quality solution

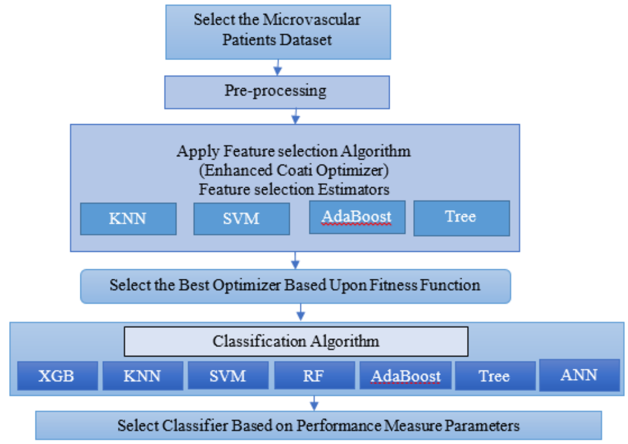

Figure 1. Proposed Approach for Predicting Microvascular Disease

4. RESULTS AND DISCUSSION

The proposed feature selection algorithm provides optimal results on the Adaboost estimator. Adaboost classifier based on the Meta-learning method. It is an ensemble classification algorithm that uses multiple weak learners. These weak learners calculate the weights and greater weights are given to continue to train the model until a smaller error is returned. This provides more flexibility for the feature set [73]. The design of the AdaBoost estimator for estimating features is determined by the prior knowledge. This a priori knowledge is available in the domain learning problem for decision stumps. These decision stumps are defined on the index of the features that cut the threshold and sign of the decision [74].

Positive Stump decision expressed below in eq 1-amssymb

$$h_{j,\theta+}(x) \triangleq 2I_{\{x^{(j)}\geq\theta\}} - 1 = \begin{cases} 1 \\ -1 \end{cases} \quad if \;\; x^{j} \geq \theta \qquad (1)$$

The negative Stump decision is expressed below in eq 2-

$$h_{j,\theta-}(x) \triangleq -h_{j,\theta+(x)} = 2I_{\{x^{(j)}<\theta\}} - 1 = \begin{cases} 1 \\ -1 \end{cases} \quad if \;\; x^{j} < \theta \qquad (2)$$

In the coati algorithm, the optimal solution is found based upon a predefined search space not concerned with the most relevant features. The main purpose of the coati optimizer is to select the best solution within the predefined search space. The Adaboost estimator is an ensemble model that builds strong classifiers from several weak classifiers. For that, it uses the weak classifiers in the series and builds the training model first. Another model works upon the error correction which is present in the first model.

This error-correcting and generating results from weak classifiers is continuous and the model is added until the complete training set is not predicting correctly. In short, it adds the maximum number of models are added. Due to this approach, the model accuracy improves also the model doesn't suffer from overfitting issues. Apart from its accuracy and overfitting issues, it deals with the problem of imbalanced data due to the boosting method. This estimator increases the interpretability of the model by dividing the model for the decision-making process into multiple processes. In the Adaboost estimator, estimation works on the stage-wise gathering of multiple weak learners together for the formation of a strong classifier. The value of the second model in the Adaboost ensemble learning model is indirectly proportional to the error of the weak learner. The mathematical model for the Adaboost estimator is given below in Equation 3:

$$S(x) = sign\left(\sum_{\mu=1}^{M} \lambda_\mu \phi_\mu(x)\right) \tag{3}$$

Where λ_μ weights for learning, when $\lambda_\mu = 0$ corresponding classifier $\phi_\mu(x)$ is not selected

The weak classifiers' data $\phi_\mu(x)$ divides the data into two parts: correctly classified or wrongly classified.

The mathematical expression for correctly classified weak classifiers is expressed in equations 4 and 5 respectively.

$$W^{+} = \left\{i : y^i \phi(x^i) = 1\right\} \tag{4}$$

$$W_{\mu}^{-} = \left\{i : y^i \phi_\mu(x^i) = -1\right\} \tag{5}$$

The weights of training data are expressed in Equation 6:

The search space is represented by various parameters depending upon the features associated with the microvascular complications. Hence the output of the coati algorithm is the combination of minimum cost with maximum efficiency.

A. Diabetic Retinopathy:

The selected features for retinopathy as age, sex, BMI, BP, FPS, Family History, and Medical Adherence. The classification results are found 99.9% and 94.78% for the Random Forest algorithm for training and testing accuracy. The comparison of various classification algorithms is shown in the figure 2.

B. Diabetic Nephropathy:

The selected features for Nephropathy as Sex, SP, FPS, Family History, and Onset Age. The classification results are found 99.8% and 95.44% for the Random Forest algorithm for training and testing accuracy. The comparison of various classification algorithms is shown in Figure 3.

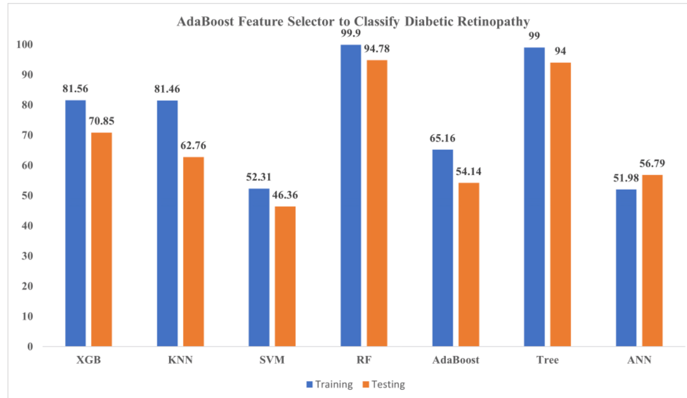

Figure 2. Comparison of Diabetic Retinopathy with XGB, KNN, SVM, RF, AdaBoost, Tree, and ANN classifier

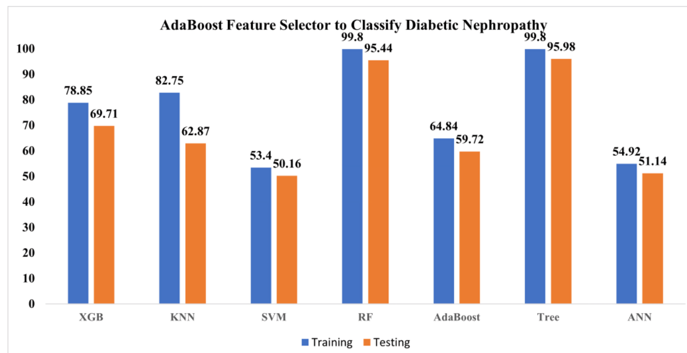

Figure 3. Comparison of Diabetic Nephropathy with XGB, KNN, SVM, RF, AdaBoost, Tree, and ANN classifier

C. Diabetic Neuropathy:

The selected features for Neuropathy are HbA1C and FPS. The classification results are found 99.8% and 95.44% for the Random Forest algorithm for training and testing accuracy. The comparison of various classification algorithms is shown in the figure 4. Table III, shows the training and testing Measuring Parameters Performance with the used

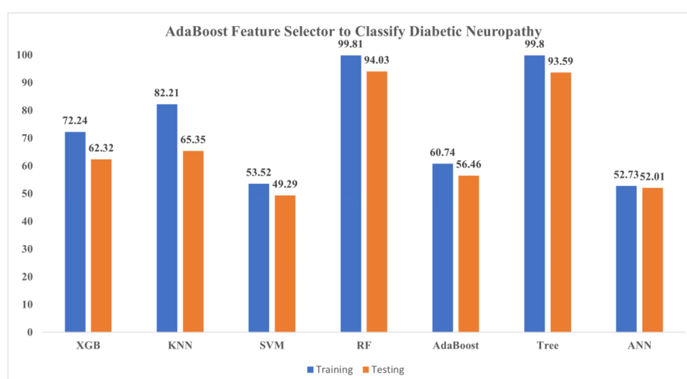

Figure 4. Comparison of Diabetic Neuropathy with XGB, KNN, SVM, RF, AdaBoost, Tree, and ANN classifier

TABLE III. TRAINING AND TESTING MEASURE PARAMETERS FOR FEATURE SELECTION ESTIMATOR AS ADABOOST WITH SELECTED FEATURES

Class	Features	Classification Algorithm	Training Accuracy	Training Precision	Training Recall	Testing Accuracy	Testing Precision	Testing Recall
Diabetic Retinopathy	Age, Sex, BMI, BP, FPS, Family History, Medical Adherence	XGB	81.5	81.6	81.5	70.5	71.6	70.5
		KNN	81.4	81.4	81.4	62.7	63.5	62.7
		SVM	52.3	61.4	52.3	46.3	46.3	46.3
		RF	99.9	99.9	99.9	94.7	94.7	94.7
		AdaBoost	65.1	65.1	65.6	56.1	56.1	56.1
		Tree	99.9	99.9	99.9	94.7	94.7	94.7
Diabetic Nephropathy	Age, Sex, SP, FPS, Family History, Onset Age	XGB	78.8	79.1	78.8	70.3	70.7	70.3
		KNN	82.7	82.7	82.7	62.8	63.0	62.8
		SVM	58.2	61.6	58.2	49.1	48.7	49.1
		RF	99.8	99.8	99.8	95.4	95.0	95.4
		AdaBoost	64.8	64.9	64.8	59.7	59.5	59.7
		Tree	99.8	99.8	99.8	95.0	95.0	95.0
Diabetic Neuropathy	HbA1C, FPS	XGB	72.2	73.2	72.2	62.3	63.1	62.3
		KNN	82.2	82.3	82.2	63.5	63.7	63.5
		SVM	52.5	52.4	52.5	43.2	43.1	43.2
		RF	99.8	99.8	99.8	94.6	94.6	94.6
		AdaBoost	60.7	60.7	60.7	56.7	56.7	56.7
		Tree	99.8	99.9	99.8	94.9	95.0	94.9

TABLE IV. COMPARISION TABLE OF RF WITH DT [15] AND PROPOSED METHODOLOGY.

Microvascular Complication	RF with DT [15]	Proposed Methodology
Diabetic Nephropathy	95.4	99.8
Diabetic Neuropathy	94.62	99.8
Diabetic Retinopathy	96.25	99.9

features for classifying the microvascular disease in type 2 diabetic patients using the Adaboost Feature Selection estimator.

For Diabetic Retinopathy, optimal results are achieved with features like Age, Sex, BMI, BP, FPS (Fast Plasma Sugar), Family History, and Medical Adherence. This suggests that a combination of demographic, physiological, and lifestyle factors contributes to accurate prediction. Conversely, for Diabetic Nephropathy, the optimal feature set includes Sex, SP (Systolic Pressure), FPS, Family History, and Onset Age, implying that genetic predisposition, blood pressure, and onset age play significant roles in nephropathy diagnosis. For Diabetic Neuropathy, HbA1C and FPS emerge as crucial predictors, emphasizing the importance of glycemic control and blood sugar fluctuations in neuropathy development. These findings underscore the complexity of diabetic complications and highlight the diverse features necessary for accurate diagnosis. Understanding the specific features associated with each complication enables targeted interventions and personalized management strategies. Moreover, these insights contribute to refining diagnostic algorithms, potentially leading to more precise and efficient healthcare interventions for diabetic patients, ultimately improving their quality of life.

Table IV, discusses RF with DT and the Proposed Methodology. The proposed methodology [15] for diagnosing different diabetic complications using a combination of Random Forest (RF) and Decision Trees (DT). The proposed method significantly improves accuracy compared to RF with DT. This indicates enhanced effectiveness in diagnosing Diabetic Nephropathy, potentially attributed to refined feature selection, improved model architecture, or optimized hyperparameters. For Diabetic Nephropathy, the proposed methodology demonstrates a substantial accuracy improvement compared to RF with DT. This suggests the robustness and generalizability of the method across different diabetic complications. Diabetic Retinopathy has high accuracy with RF and DT, but the proposed methodology still manages a notable improvement. This underscores the efficacy and versatility of the method in consistently enhancing diagnostic accuracy across various diabetic conditions. The proposed methodology consistently outperforms the baseline approach of RF with DT across all three diabetic complications. The significant improvements in accuracy highlight the methodology's potential to advance diagnostic capabilities in identifying diabetic complications, which could ultimately lead to more effective patient management and treatment strategies. Further investigation into the specific enhancements introduced by the proposed methodology would provide deeper insights into its superior performance.

5. CONCLUSION

Microvascular complications in type 2 Diabetic patients commonly occur as diabetic retinopathy, neuropathy, and nephropathy. This complication depends upon the various parameters. In the proposed system the essential parameters are extracted using AdaBoost Estimator. This Improved Enhanced Coati feature extraction selects the optimal feature selector estimator which provides the optimal result based upon the fitness function. The selected features are age, sex, BMI, BP, FPS, Family History, Medical Adherence for diabetic retinopathy, Sex, SP, FPS, Family History, Onset Age for Nephropathy, and HbA1C and FPS for Neuropathy. The proposed feature selection algorithm results best for the Adaboost feature selection algorithm and provides suitable results for training and testing accuracy for the Random Forest classifier.

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