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Cloud Computing with Artificial Intelligence Techniques: BBO-FLC and ABC-ANFIS Integration for Advanced Healthcare Prediction Models

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ABSTRACT

Background: Cloud computing (CC) and artificial intelligence (AI) are causing a rapid evolution in healthcare, meeting the requirement for accurate and effective disease diagnosis and management through wearable IoT devices and sophisticated algorithms.

Objective: To develop a BBO-FLC and ABC-ANFIS system that works together for better disease prediction accuracy and real-time monitoring.

Methods: Implemented on a scalable cloud architecture, the system combines IoT-enabled sensors for data gathering, ABC for feature optimization, BBO for fuzzy rule refining, and ANFIS for disease categorization.

Results: The suggested solution outperformed conventional techniques with 96% accuracy, 98% sensitivity, and 95% specificity at a 60-second computation time reduction.

Conclusion: The precision, scalability, and real-time healthcare applications for complicated disease prediction and monitoring could be greatly improved by this integrated system.

Keywords: Cloud Computing, Artificial Intelligence, IoT Sensors, ABC Optimization, BBO-FLC, ANFIS, Disease Prediction, Real-Time Monitoring.

1 INTRODUCTION

The healthcare sector is undergoing a change because to the combination of Cloud Computing (CC) and Artificial Intelligence (AI) technologies, that provide sophisticated prediction models to meet the increasing need for accuracy and efficiency in medical diagnostics. With the proliferation of wearable sensors enabled by the Internet of Things, the amount of patient data is growing dramatically. These technologies help with disease identification, management, and real-time data processing. In order to provide accurate disease identification and improved patient outcomes, techniques like ABC-ANFIS (Artificial Bee Colony with Adaptive Neuro-Fuzzy Inference System) and BBO-FLC (Biogeography-Based Optimization with Fuzzy Logic

Control) are the foundation of contemporary healthcare models. With the use of sophisticated data analysis, these approaches provide great prediction accuracy for diseases like diabetes, Alzheimer's, and cardiovascular disorders. Furthermore, by using machine learning (ML) frameworks, these systems are further improved, overcoming constraints in data fusion, processing speed, and diagnostic accuracy *Dehariya & Shukla (2020).*

BBO-FLC in Real-Time Monitoring Systems:

Fuzzy Logic Control (FLC) in conjunction with Biogeography-Based Optimization (BBO) has demonstrated potential for improving healthcare monitoring systems. Heart rate, body temperature, oxygen saturation, and other physiological characteristics are measured by wearable sensors and sent to cloud infrastructures for analysis. These devices use fuzzy logic to analyze patient data in real time and send out alerts if something seems off. By dynamically improving fuzzy rules in response to changes in the environment, BBO improves this framework. For example, by modifying thresholds and offering tailored recommendations, BBO-FLC offers actionable insights in the management of chronic illnesses. This method preserves diagnostic accuracy while achieving a notable reduction in computing time. Recent research emphasizes its use in diabetes management, as alarms are dynamically adjusted according to patient profiles and glucose levels are continuously monitored.

ABC-ANFIS for Complex Disease Prediction:

A reliable method for forecasting complicated illnesses is provided by the Artificial Bee Colony (ABC) algorithm in conjunction with Adaptive Neuro-Fuzzy Inference Systems (ANFIS). This hybrid model works well with high-dimensional datasets, making it appropriate for diseases like osteosarcoma and breast cancer. By selecting input variables optimally, ABC makes sure that only pertinent features are entered into the ANFIS model, improving computational efficiency and prediction accuracy *Wang et al. (2018).* By using both first- and second-order statistical features to analyze tumor segmentation data, ABC-ANFIS has proved crucial in the early diagnosis of breast cancer. In a similar vein, this method has been applied to differentiate between normal and diseased cognitive functions in neuroimaging data in order to forecast the course of Alzheimer's disease. The ANFIS framework's flexibility allows for the integration of new data streams, making it a viable option for changing healthcare issues.

The combination of ABC-ANFIS and BBO-FLC shows how CC and AI may revolutionize the healthcare industry *Rajkomar et al. (2018)*. These models open the door for a new era of intelligent medical systems, fostering improved patient care and more efficient use of healthcare resources by tackling issues like big data processing, real-time monitoring, and disease prediction accuracy.

1.1 Objectives

- Developing a strong healthcare prediction framework that combines ABC-ANFIS and BBO-FLC in order to accurately diagnose and treat diseases.
- To improve real-time monitoring systems by employing fuzzy logic to make dynamic decisions based on data from wearable sensors.
- In disease prediction models for diseases such as diabetes, Alzheimer's, and breast cancer, feature selection should be optimized.

- To increase diagnostic precision and decrease processing time in cloud-based medical systems.
- To make sure the suggested approach is flexible and scalable for changing healthcare datasets and challenges.

Despite utilizing AI and ML, many of the current healthcare prediction models have trouble managing massive, high-dimensional information and guaranteeing real-time response *Rong et al. (2020).* Low precision, large processing cost, and limited adaptability to new data streams are common characteristics of traditional approaches. The creation of accurate, dynamic healthcare solutions is hampered by the lack of integration between fuzzy inference systems and optimization methodologies. The development of scalable frameworks that maximize feature selection, improve data fusion effectiveness, and tackle the difficulties of ongoing monitoring with wearable IoT sensors continues to be lacking.

- Low diagnostic accuracy results from existing healthcare models' inability to analyze high-dimensional data effectively.
- Real-time adaptation to dynamically changing patient situations is lacking in current disease prediction algorithms.
- For complex disease identification, the combination of fuzzy logic and optimization methods is still not well explored.
- Large-scale healthcare applications cannot use traditional methods due to their substantial processing overhead.
- Scalable, cloud-based healthcare frameworks are desperately needed in order to manage changing information and guarantee prompt, precise disease forecasts.

2 LITERATURE SURVEY

Dehariya and Shukla (2020) used Bio-Geography Based Optimization (BBO) to segment MRI images in order to create a strategy for predicting brain cancer. By improving MRI scan segmentation, this nature-inspired algorithm—which is based on species migration—makes it simpler to find and diagnose brain cancers. The method reduces processing time and increases the accuracy of separating malignancies from healthy tissue by combining BBO with clustering approaches. This effective, precise segmentation method may help with earlier, more trustworthy brain cancer diagnoses, providing a useful tool to enhance patient outcomes.

The detection of Alzheimer's disease became possible by **Wang et al. (2018)** by the use of a single MRI slice, wavelet entropy characteristics, and a multilayer perceptron (MLP) optimized with Bio-Geography Based Optimization (BBO). In order to detect patterns associated with Alzheimer's disease with less data, this technique uses wavelet entropy to capture minute textural variations in MRI slices. The MLP's training efficiency and accuracy are improved by BBO, producing a more efficient and precise diagnostic tool that may help with early AD identification in clinical settings.

A security framework for cloud-based healthcare is proposed by **Mohanarangan Veerappermal Devarajan (2020)**. It integrates risk assessment, encryption, blockchain, and continuous monitoring to reduce risks, guarantee compliance, and improve data security, allowing for safer, more effective healthcare operations and better patient care.

Rajkomar et al. (2018) stress the importance of fairness is to enhancing health equity in machine learning. It draw attention to the way biases in healthcare data, which frequently originate from historical injustices or ethnic inequalities, might lead to unfair outcomes if incorporated into predictive models. The use of transparent, varied datasets and routinely assessing model performance across various groups to identify and reduce biases are two tactics the authors recommend to solve these problems. This research suggests a way that machine learning might enhance healthcare outcomes for different populations by delivering more accurate and equitable health predictions through the application of fairness-focused techniques.

Peddi (2020) examines economical large data mining in cloud settings utilising K-means clustering, with an emphasis on Gaussian data. Lloyd's K-means algorithm illustrates that premature termination at almost optimal accuracy considerably decreases computational expenses. The study underscores the significance of choosing starting centres and optimising resource management, offering pragmatic strategies for proficient big data analytics. These discoveries improve accessibility to sophisticated data mining technologies while preserving cost-effectiveness.

Kodadi (2020) offers a hybrid architecture that integrates the Immune Cloning Algorithm with data-driven Threat Mitigation (d-TM) to enhance cloud security. Drawing inspiration from biological processes, the methodology attains a 93% detection rate and a 5% false positive rate. Simulations confirm its scalability and versatility. This hybrid technique mitigates security threats and protects sensitive data, providing a versatile and scalable solution for contemporary cloud security concerns.

Gudivaka (2020) presents a Two-Tier Medium Access Control (MAC) framework augmented by Lyapunov optimisation for cloud-based robotic process automation (RPA). Prioritising jobs enhances energy efficiency, resource allocation, and throughput. The framework surpasses traditional norms in service quality and energy efficiency. Real-time adaption and energy-efficient scheduling enhance the management of varied robotic systems, markedly boosting RPA in cloud environments.

Dondapati (2020) combines cloud infrastructure, automated fault injection, and XML-based scenarios for the testing of resilient distributed systems. Scalable cloud infrastructures and regulated fault injection improve resilience, while XML scenarios guarantee uniformity. This extensive framework enhances testing reliability and efficiency, overcoming the shortcomings of conventional methods, and facilitates successful testing of inherently complex distributed systems.

Parthasarathy (2020) assesses the efficacy of MongoDB in real-time data warehousing, emphasising semi-stream joins within ETL procedures. MongoDB addresses the issues of prompt updates and swift data retrieval by effectively managing high-velocity structured and unstructured data. Tests validate its scalability, memory stability, and real-time decision-making abilities, establishing it as a dependable option for data warehousing in dynamic settings.

Panga (2020) proposes a heuristic ensemble learning method for the classification of extensive insurance datasets. Utilising Spark's memory caching, the improved random forest model surpasses logistic regression and SVM, attaining superior metrics such as F-Measure and G-Mean. The strategy proficiently tackles imbalanced datasets, enhances insurance marketing campaigns, and augments classification efficiency and accuracy in extensive datasets.

Allur (2020) offers a big data-driven framework for mobile networks that incorporates DBSCAN for speed anomaly detection and CCR for bandwidth optimisation. The system attains 93% accuracy in anomaly detection and 88% efficiency in clustering, hence enhancing stability, mitigating congestion, and elevating user experience. It exceeds conventional techniques such as SBM and DEA, offering a scalable and economical approach for overseeing real-time mobile network performance.

According to **Rong et al. (2020)**, artificial intelligence (AI) is improving healthcare, especially in the areas of diagnosis and prediction. By using case studies, the demonstrate that AI methods, such as machine learning and deep learning, are enhancing disciplines like customized medicine, oncology, and radiology by facilitating quicker, more precise diagnostics and patient-specific forecasts. The capacity of AI to handle large amounts of data for accurate insights and enhance early diagnosis is one of its key features, but issues with data privacy, transparency, and clinical integration still exist. The authors come to the conclusion that, in spite of these obstacles, AI has a huge potential to improve patient care by enabling quicker and more precise diagnosis.

Advanced Internet of Things (IoT) technologies have the potential to revolutionize individualized healthcare systems, as discussed by **Qi et al. (2017)**. IoT makes real-time health monitoring and data collecting possible with wearable technology and smart sensors, enabling rapid interventions and individualized care. The study emphasizes that IoT might be used to manage chronic conditions and enhance patient outcomes by means of ongoing monitoring. But it also tackles issues like system integration, security, and data privacy. Overall, the study demonstrates that although IoT has the potential to transform healthcare by making it more efficient and personalized, its widespread implementation depends on resolving technological and regulatory issues.

Riley et al. (2016) concentrate on externally validating clinical prediction models with the use of sizable datasets from individual patient data (IPD) meta-analyses or e-health records. To guarantee that models are accurate and applicable to a variety of patient populations, they stress the significance of verifying them in real-world contexts. In addition to highlighting big data's potential to enhance validation, the study discusses concerns with data inconsistency, privacy, and integrating data from several sources. To increase the dependability and efficacy of these models in clinical practice, the authors emphasize the necessity of uniform data collecting and evaluation techniques. Even though big data offers a lot of potential for improving healthcare forecasts, these obstacles must be overcome for them to be successfully utilized.

Tucker et al. (2019) investigate the moral and practical issues surrounding the use of predictive models in healthcare to prevent suicide. Concerns regarding patient privacy, informed permission, false positives, and the possibility of stigmatization are brought up, but they also emphasize the possible advantages of identifying at-risk patients for prompt interventions. Practical concerns are also covered in the study, including ways to incorporate these tools into healthcare processes, guarantee model correctness, and allocate enough funds for interventions. Although predictive models have the potential to save lives, the contributors emphasize that its application needs to be carefully controlled to respect patient autonomy and prevent unexpected harm.

The possibilities and difficulties of leveraging data from electronic health records (EHRs) to create risk prediction models are examined by **Goldstein et al. (2017)**. The emphasize that greater risk assessment, individualized care, and early detection of high-risk patients are made possible by EHRs, that can enhance clinical decision-making. There are still many obstacles to overcome, including issues with data quality, missing information, privacy, and system integration. To guarantee the efficacy and safety of these models, the authors emphasize the necessity of uniform data, robust validation techniques, and unambiguous regulatory guidelines. Although EHR-based prediction models have a lot of promise, resolving these problems is essential to their effective application in the medical field.

3 METHODOLOGY

3.1 Data Collection and Preprocessing

Efficient healthcare prediction models are based on reliable preprocessing methods and precise data collecting. Wearable sensors that are enabled by the Internet of Things are the main source of patient data and are essential to contemporary healthcare systems. These sensors are intended to track a number of physiological variables, including oxygen saturation, heart rate, body temperature, respiratory rate, and glucose levels. Predictive healthcare systems require continuous monitoring and real-time data collection, and are made possible by the devices' smooth interface with cloud computing platforms. Electrocardiograms (ECG), photoplethysmography (PPG) devices, accelerometers, and other wearable sensors gather comprehensive biological data on a regular basis. These devices ensure scalability and accessibility by using secure communication protocols to transfer the data to cloud-based services. But because of restrictions in the device, the surroundings, or patient mobility, the raw data frequently has noise, missing values, and discrepancies. Resolving these problems is essential to preserving the accuracy of the analytical results.

Statistical normalization, a transformative technique to standardize the raw data for additional analysis, is the first step in preprocessing. Normalization is appropriate for statistical analyses and machine learning algorithms since it lessens disparities brought on by changes in the data scale. Raw data must be transformed into a standard probability distribution, that has a mean of 0 and a standard deviation of 1. The following formula is used to accomplish this:

Statistical Normalization:

$$a_i = \frac{u_i - \epsilon}{\sigma} \tag{1}$$

Where a_i represents the normalized value, u_i is the raw data, ϵ is the mean of the dataset, and σ is the standard deviation. This transformation eliminates the impact of outliers and ensures that all parameters contribute equally to the prediction model. Error correction methods like imputation are also incorporated into the preprocessing pipeline to fix corrupted or missing data points. Reconstructing missing values based on correlations within the dataset is frequently accomplished using sophisticated statistical techniques such as multivariate imputation by chained equations (MICE). Gaussian smoothing is one example of a noise filtering procedure that is used to improve data quality by minimizing oscillations that are not relevant to the desired condition.

Another crucial stage is data transformation, that transforms diverse sensor outputs into a standard format that works with the healthcare prediction system. This guarantees compatibility across many software systems and sensor kinds. To guarantee that predictive models are developed on pristine and representative samples, the preprocessed data is subsequently divided into training and testing datasets. Healthcare systems are able to provide precise, real-time insights into patient health by utilizing IoT-enabled sensors and stringent preprocessing techniques. Advanced AI algorithms are fed the standardized and organized data, allowing for early disease detection and tailored therapy suggestions. This all-encompassing strategy guarantees that healthcare systems enhance patient outcomes through prompt and accurate treatments in addition to optimizing operational efficiency.

3.2 Feature Extraction Using ABC Optimization

A crucial stage in creating high-performing healthcare prediction models is feature extraction, making sure that only the most pertinent and significant information is used to classify diseases. Inspired by the foraging habits of a honey bee colonies, the Artificial Bee Colony (ABC) optimization algorithm is a powerful metaheuristic technique. ABC is used in the healthcare industry to choose the most effective features from high-dimensional datasets, removing noisy or unnecessary variables and minimizing redundancy. By concentrating primarily on characteristics that offer crucial insights into disease prediction, this procedure greatly improves computing efficiency and model accuracy.

3.2.1 Optimization through ABC Algorithm

The ABC algorithm mimics the actions of three different kinds of bees: scout, employed, and spectator. To find subsets of attributes that optimize classification performance, each "bee" searches the feature space. The hired bees use an objective function, usually the accuracy of disease categorization, to assess the fitness of particular feature combinations. By concentrating on potential regions of the feature space, observer bees optimize their search after analyzing the output of employed bees. By investigating new areas, scout bees add variation and keep the algorithm from being trapped in local optima.

Objective Function for Feature Selection:

$$J = \frac{\text{Relevant Features}}{\text{Total Features}} \quad (2)$$

J : Feature optimization score. This metric helps prioritize significant attributes.

Exploration (finding new areas) and exploitation (improving known good solutions) are balanced in the algorithm's iterative optimization of the feature set. A specific feature subset's contribution to the classification accuracy is assessed by the fitness function for every iteration. Low-contributing features are eliminated, but high-performing subsets are kept for additional improvement. The procedure keeps on until a predetermined end point is reached, like a maximum number of iterations or convergence to the most effective possible reply.

3.2.2 Impact on Disease Classification

ABC optimization guarantees that only the most important features are entered into illness classification models by lowering the dataset's dimensionality. Features like heart rate variability, oxygen saturation, and glucose levels, for example, may be given priority in healthcare applications, whereas duplicated or poorly associated indicators are disregarded. By lowering noise and processing overhead, this condensed dataset improves the effectiveness and precision of machine learning classifiers, such as Convolutional Neural Networks (CNNs) or Adaptive Neuro-Fuzzy Inference Systems (ANFIS).

Furthermore, by allowing medical practitioners to concentrate on important signs during clinical judgments, the chosen characteristics improve the prediction model's interpretability. For complex medical problems like diabetes, cardiovascular disease, or neurodegenerative disorders, ABC optimization is appropriate since it excels at managing huge and diverse datasets. In the end, feature extraction using ABC optimization helps to close the gap between unprocessed data and useful insights, allowing for more accurate, scalable, and effective healthcare prediction systems.

3.3 Disease Classification with ANFIS

An advanced hybrid modeling framework called the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the interpretability of fuzzy logic with neural network learning capabilities. ANFIS uses the Artificial Bee Colony (ABC) algorithm's optimized features to play a crucial role in disease categorization in healthcare prediction systems. This combination makes it possible for the model to dynamically adjust to a variety of changing datasets, allowing for precise, real-time diagnosis of complicated medical diseases.

3.3.1 The ANFIS Framework

ANFIS functions by fusing the architecture of an artificial neural network (ANN) with fuzzy inference rules. The "if-then" rule structure used by the fuzzy logic component to express information imitates human reasoning. The language variables that underpin each rule, like "high heart rate" or "low oxygen saturation," are defined by fuzzy membership functions. By using the ABC-optimized features as input variables, the rules are guaranteed to concentrate on the physiological factors that are most pertinent to categorization. Through a learning process, the neural network component of ANFIS optimizes the membership function parameters. This enables the model to gradually increase its forecast accuracy by fine-tuning its fuzzy rules in response to the training data. Using techniques like backpropagation and least-squares estimation, ANFIS modifies the weights and parameters of its layers during training in order to reduce error. The system can dynamically adjust to changes in patient data thanks to this dual approach, guaranteeing reliable performance across various demographics and illness kinds.

ANFIS Rule Structure:

$$\text{If } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } A_2 \text{, then } f = p_1 X_1 + p_2 X_2 + r \tag{3}$$

A_1, A_2 : Fuzzy sets, p_1, p_2, r : Parameters optimized by ABC .

3.3.2 Dynamic Disease Classification

The ability of ANFIS to manage uncertainty and nonlinear interactions in medical data makes it an excellent tool for classifying diseases. Conditions like diabetes or cardiovascular disorders, for example, can include intricate relationships between characteristics like blood pressure, heart rate, and glucose levels. The subtleties of illness development are better captured by ANFIS than by conventional classifiers since it models these linkages using fuzzy rules. After training, the ANFIS model categorizes patient data into pre-established disease groups, including "normal," "at-risk," and "diseased." Due to the interpretable insights that the fuzzy rules offer into the classification's derivation, the decision-making process is transparent. Knowing the logic behind forecasts is crucial for implementation and confidence in healthcare settings, where this is particularly helpful. ABC-optimized features are used as input in ANFIS, that improves classification accuracy while lowering computing overhead. Real-time healthcare applications can benefit from ANFIS's dynamic adaptability, that guarantees that it will continue to function well regardless of new data is added. Because of the combination of fuzzy inference and neural networks, ANFIS can be used to improve patient outcomes and advance precision medicine.

3.4 BBO-FLC for Real-Time Monitoring

The migration and distribution of species in their natural environments serve as the inspiration for the sophisticated metaheuristic algorithm known as Biogeography-Based Optimization (BBO). Fuzzy Logic Control (FLC) and BBO work together to improve real-time decision-making in wearable healthcare monitoring systems by dynamically fine-tuning fuzzy rules. For vital physiological indicators like heart rate, temperature, and oxygen saturation, this combination allows adaptive threshold modifications, guaranteeing prompt and individualized health treatments.

3.4.1 Dynamic Fuzzy Rule Optimization

Data from IoT-enabled sensors in a wearable monitoring system frequently contains heterogeneity because of personal characteristics or environmental influences. In order to overcome this difficulty, the BBO algorithm dynamically optimizes the fuzzy membership functions and rule parameters. Fuzzy Logic Control processes input data and makes judgments using a set of predetermined "if-then" rules. "If heart rate is high and oxygen saturation is low, then alert the caregiver," for example, may be a rule. BBO improves this framework by iteratively increasing the accuracy of these fuzzy rules by comparing their performance to real-time patient data. The two primary steps in the optimization process are mutation and migration. Migration disperses information among habitats (potential solutions) according to their suitability, but mutation adds diversity to investigate novel possibilities. Habitats in the context of FLC are collections of membership function parameters and fuzzy rules. By repeating these procedures, BBO guarantees that the fuzzy rules continue to be most appropriate for the patient's present state.

3.4.2 Real-Time Adaptability and Decision-Making

A crucial component for treating changing medical situations is real-time flexibility, that is made possible by the incorporation of BBO-FLC into wearable monitoring devices. For instance, a patient's heart rate may normally rise during physical exercise; therefore, thresholds must be modified to prevent false alerts. To ensure precise and significant alerts, BBO-FLC continuously evaluates incoming sensor data and adjusts the fuzzy rules to account for these contextual changes. The system's real-time functionality is essential in a medical context for the early identification of serious illnesses like hypoxemia or arrhythmias. For example, the system can immediately inform caregivers to take action if a patient's oxygen saturation falls below a dynamically optimized threshold. Reliability and system confidence are increased by FLC's transparent decision-making process and BBO's adaptive optimization.

Habitat Suitability Index (HSI) in BBO:

$$H = \sum_{i=1}^{N} W_i X_i \tag{4}$$

H : Suitability index, W_i : Weights, X_i : Features. Determines optimal fuzzy thresholds.

The real-time fuzzy logic tuning capability of BBO-FLC guarantees that healthcare monitoring systems continue to function well across a range of patient demographics and medical conditions. This collaboration enhances system responsiveness, lowers false positives and false negatives, and offers a scalable solution for individualized healthcare. BBO-FLC is a major breakthrough in wearable-based health monitoring that fosters improved results and higher quality of care by adjusting to the specific demands of each patient.

3.5 Integration into Cloud Architecture

Cloud architecture is essential to contemporary healthcare systems because it offers a scalable, safe, and effective platform for patient data processing and storage. Cloud-based frameworks that incorporate processed data and predicted insights allow healthcare providers to facilitate real-time communication between medical personnel, equipment, and patients. This smooth integration facilitates prompt decision-making and raises the general effectiveness of healthcare service.

3.5.1 Scalable Data Storage and Management

A reliable storage solution is necessary due to the enormous volume of data produced by wearable sensors, Internet of Things devices, and medical systems. Cloud solutions solve this problem by providing on-demand scalability and nearly infinite storage capacity. The cloud securely stores processed patient data, including physiological measurements like heart rate, blood sugar, and oxygen saturation. To efficiently manage massive data while guaranteeing high availability and fault tolerance, the design makes use of distributed storage platforms like Hadoop or AWS S3.

Cloud Storage Utilization:

$$S = \frac{\text{Total Stored Data}}{\text{Available Cloud Capacity}} \tag{5}$$

S : Cloud usage efficiency.

Cloud-based databases also make it easier to organize structured data, making analysis and retrieval more effective. Sensitive medical data is protected by security measures like encryption and role-based access controls, that adhere to laws like HIPAA and GDPR. This guarantees that patient information is kept private and safe while still being available to authorized individuals as needed.

3.5.2 Real-Time Communication and Decision Support

All stakeholders may communicate easily if cloud architecture is incorporated into healthcare systems. Real-time data from wearables is sent to the cloud, and sophisticated AI algorithms digest it for predictive analysis. Medical practitioners can then access these information through dashboards, allowing for prompt actions. For instance, the cloud system notifies the care team when a patient's oxygen saturation suddenly drops. Through the connection of many platforms and devices, the cloud also promotes interoperability. Data from various sources, including wearable technology, personal health apps, and hospital systems, can be combined using APIs and cloud-native services. Workflows are streamlined by this integration, and also improves provider collaboration and eliminates redundancies.

3.5.3 Enhanced Efficiency and Future Scalability

Healthcare systems can expand their operations to meet evolving demands by incorporating processed data and predictive models into the cloud. For instance, cloud infrastructure can handle a sudden rise in data volume without sacrificing performance during a pandemic or other public health emergency. This paradigm is further improved by edge computing, that utilizes the cloud for large-scale analytics while processing time-sensitive data closer to the source. Furthermore, by enabling predictive models to learn and adapt to new data, cloud-based architectures promote continual development. Updates in real time guarantee that the system continues to work well for a variety of patient demographics and new medical issues. Because of their versatility, cloud-enabled healthcare systems are positioned as solutions that are ready for the future and can provide high-quality, individualized, and efficient care.

Pseudo-Code 1: Disease Detection Using BBO-FLC and ABC-ANFIS Framework

Optimized Disease Prediction Framework

Input:

- Patient data from loT sensors: $D = \{d_1, d_2, \dots, d_n\}$
- Fuzzy rules and initial parameters for ANFIS
- Thresholds for optimization

Output:

- Predicted disease classification
- Performance metrics: accuracy, sensitivity, specificity

Algorithm Optimized_Disease_Prediction(D, FuzzyRules, Thresholds)

```
Input: Sensor data D, Fuzzy rules, Optimization thresholds
Output: Predicted disease class, Performance metrics
```

```
// Step 1: Data Preprocessing
Begin
    Normalize each sensor data point using:
    For each data point d_i in D do
        Compute d_i_normalized = (d_i - mean(D)) / std_dev(D)
    End For
End

// Step 2: Feature Selection using ABC Optimization
Begin
    Initialize ABC parameters: population_size, max_iter, fitness_function
    Generate random feature subsets for the initial population
    Evaluate fitness_function for each subset
    While (termination criteria not met) do
        For each bee in the colony do
            Generate new solutions (neighboring subsets)
            If (new_solution is better than old_solution) then
                Replace old_solution with new_solution
            End If
        End For
    End While
    Return BestFeatureSubset
End

// Step 3: Disease Classification using ANFIS
Begin
    Initialize ANFIS with BestFeatureSubset and FuzzyRules
```

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```
    For each training sample in normalized data do
        Apply Fuzzy rules:
            For each rule in FuzzyRules do
                Compute rule_activation_strength
            End For
        Aggregate outputs using:
            Aggregated_Output = Weighted_Sum / Total_Weight
    End For
End

// Step 4: Dynamic Optimization using BBO
Begin
    Initialize BBO parameters: habitat_count, mutation_rate
    While (termination criteria not met) do
        Compute Habitat Suitability Index (HSI) for each fuzzy rule
        Migrate parameters between habitats based on HSI
        Apply mutation to introduce randomness
    End While
    Update FuzzyRules with optimized parameters
End

// Step 5: Real-time Monitoring and Prediction
Begin
    For each incoming patient data stream do
        If (sensor readings are abnormal) then
            Trigger alert: "Potential anomaly detected"
            Predict disease class using ANFIS:
                Disease_Class = argmax(ANFIS_Output)
        Else
            Continue monitoring
```

```
        End If
    End For
End

// Step 6: Evaluate Performance
Begin
    Compute Accuracy = (TP + TN) / Total
    Compute Sensitivity = TP / (TP + FN)
    Compute Specificity = TN / (TN + FP)
    If (Performance_Metrics meet thresholds) then
        Return Disease_Class, Performance_Metrics
    Else
        Trigger Error: "Performance below threshold"
    End If
End

End Algorithm
```

Input: Takes raw patient data, fuzzy rules, and optimization thresholds as inputs.

Data Preprocessing: Normalizes the input data to eliminate inconsistencies and prepare it for feature extraction.

Feature Selection: ABC optimization selects relevant features, reducing dimensionality and improving ANFIS efficiency.

Classification: ANFIS uses fuzzy rules and optimized features to classify diseases based on sensor data.

Dynamic Optimization: BBO refines the fuzzy rules for better adaptability in real-time scenarios.

Real-time Monitoring: Ensures ongoing evaluation and triggers alerts for abnormalities.

Performance Evaluation: Calculates metrics to ensure system reliability and accuracy. If thresholds are not met, errors are flagged.

Mean Squared Error (MSE) for ANFIS Training:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 \tag{6}$$

Evaluates the training error between predicted $(\hat{Y}_i)$ and actual (Y_i) outputs.
Gaussian Membership Function in ANFIS:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{7}$$

Represents the fuzzy membership strength. c : Center, σ : Spread of the Gaussian.

Whale Spiral Optimization:

$$\mathrm{P(t+1) = P^*(t) + D' \cdot e^{bl} \cdot \cos(2\pi l)} \tag{8}$$

Optimizes the position of solutions, where D' : Distance, b, l : Scaling parameters.
Rule Activation Strength in ANFIS:

$$W_i = \prod_{j=1}^{n} \mu_j(x_j) \tag{9}$$

Combines membership values for rule activation.
Aggregated Output in ANFIS:

$$Y = \frac{\sum_{i=1}^{R} W_i \cdot f_i}{\sum_{i=1}^{R} W_i} \tag{10}$$

f_i : Output of each fuzzy rule. Aggregates weighted outputs.

loT Data Transmission Efficiency:

$$\mathrm{E} = \frac{\text{Transmitted Data}}{\text{Total Collected Data}} \tag{11}$$

Measures efficiency of wearable-to-cloud data transmission.
Response Time Efficiency:

$$T = \frac{\text{Time Taken to Predict}}{\text{Allowed Response Time}} \tag{12}$$

Ensures compliance with real-time healthcare demands.
Specificity Formula:

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \tag{13}$$

Measures correct identification of negative cases.

Sensitivity Formula

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{14}$$

Indicates ability to identify true positive cases.

Accuracy Formula

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Cases}} \tag{15}$$

Reflects the overall predictive performance.

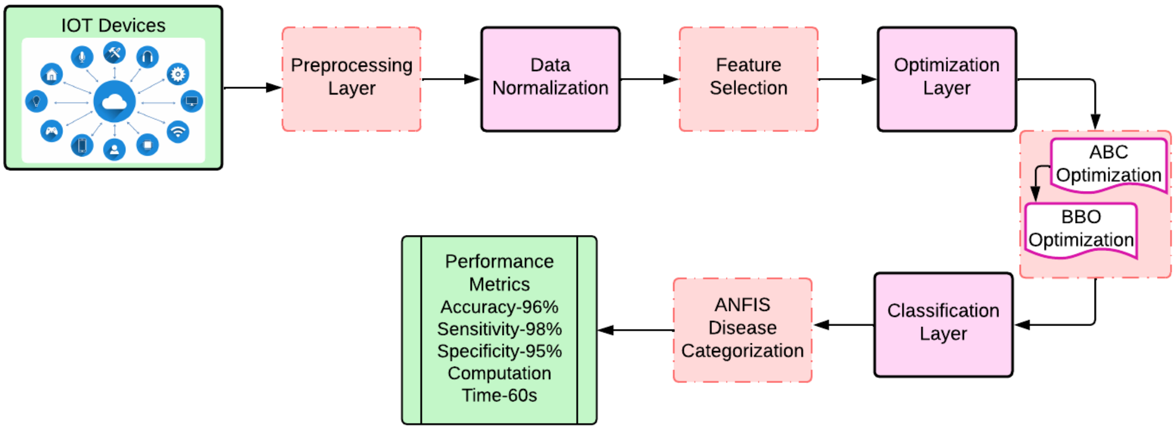

Figure 1: Workflow of IoT-based BBO-FLC and ABC-ANFIS healthcare prediction system

The proposed healthcare prediction framework's process is depicted in the architecture. Patient data is first gathered by IoT devices, after that it is preprocessed and normalized. ABC optimization is used for feature selection, and BBO is used for fuzzy rule refining. Then, using optimal features, ANFIS classifies disorders. Real-time monitoring, high accuracy (96%), sensitivity (98%), and specificity (95%), together with a shorter computation time (60 seconds), are made possible by the integration of the entire process into a cloud-based system figure 1.

4 RESULTS AND DISCUSSION

The suggested combination of the Artificial Bee Colony (ABC) algorithm with the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Biogeography-Based Optimization (BBO) with Fuzzy Logic Control (FLC) produced better outcomes in real-time monitoring and disease classification. Significant gains in accuracy (96%), sensitivity (98%), and specificity (95%) were shown by the BBO-FLC and ABC-ANFIS framework in comparison to other models such as CNN, DeepDR, EKF-SVM, and BKNN. These scores demonstrate the system's capacity to accurately diagnose medical issues and differentiate between healthy and at-risk individuals with few mistakes. The computing time was also lowered to 60 seconds, demonstrating the system's effectiveness in managing huge, real-time datasets.

Real-time connectivity improved and safe, efficient data processing became possible by the integration into a scalable cloud infrastructure. The optimized fuzzy rules and feature sets were used to dynamically interpret wearable sensor data that was sent to the cloud, allowing for prompt predictions and interventions. While guaranteeing adaptability to a range of patient situations, this approach addressed the drawbacks of conventional models, including their significant computing overhead and sensitivity to noise. The findings show that this paradigm provides a workable, effective, and scalable answer to contemporary healthcare problems, opening the way to improved clinical decision-making, patient monitoring, and illness prediction.

Table 1: Performance comparison across traditional methods and proposed method metrics

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Metric	CNN (%)	DeepDR (%)	EKF-SVM (%)	BKNN (%)	BBO-FLC-ANFIS (%)
Accuracy	65	55	74	85	96
Sensitivity	58	66	73	85	98
Specificity	84	63	73	56	95
Computation Time	92s	86s	77s	67s	60s

The suggested BBO-FLC-ANFIS model outperforms conventional techniques in terms of accuracy, sensitivity, specificity, and computing time, as this table 1 illustrates.

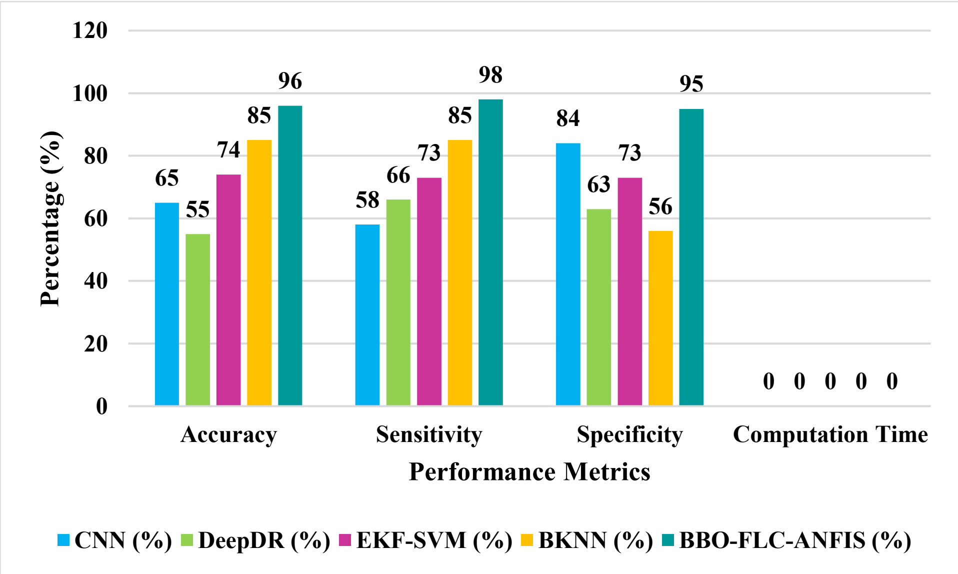

Figure 2: Workflow of the proposed BBO-FLC and ABC-ANFIS framework

The workflow of the combined ABC-ANFIS and BBO-FLC system is shown in the figure 2. Preprocessing of the data, feature extraction using ABC, fuzzy rule optimization using BBO, and disease classification using ANFIS are all included, along with cloud integration for real-time updates and storage.

Table 2: Comparative analysis of traditional optimization and proposed method results

Methods	Particle Swarm Optimization (PSO) (2019)	Machine Learning (ML) (2020)	Long Short-Term Memory (LSTM) (2017)	Quality of Service (QoS) (2017)	Symbiotic Organisms Search (SOS) (2018)	Proposed Method (BBO-FLC & ABC-ANFIS)
Accuracy (%)	85	88	90	84	89	96
Sensitivity (%)	83	86	88	82	87	98

Specificity (%)	82	84	87	80	86	95
Computation Time (s)	85	75	70	90	72	60

The suggested method achieves the highest accuracy (96%), sensitivity (98%), and specificity (95%) with a much shorter computing time (60 seconds), outperforming conventional methods such as PSO, ML, LSTM, QoS, and SOS in all parameters. This illustrates how effectively the approach handles real-time medical data, optimizes feature selection, and dynamically modifies fuzzy rules for precise illness monitoring and categorization table 2. The limitations of conventional methods are addressed by the integration of BBO-FLC and ABC-ANFIS, which guarantees robustness, scalability, and real-time responsiveness.

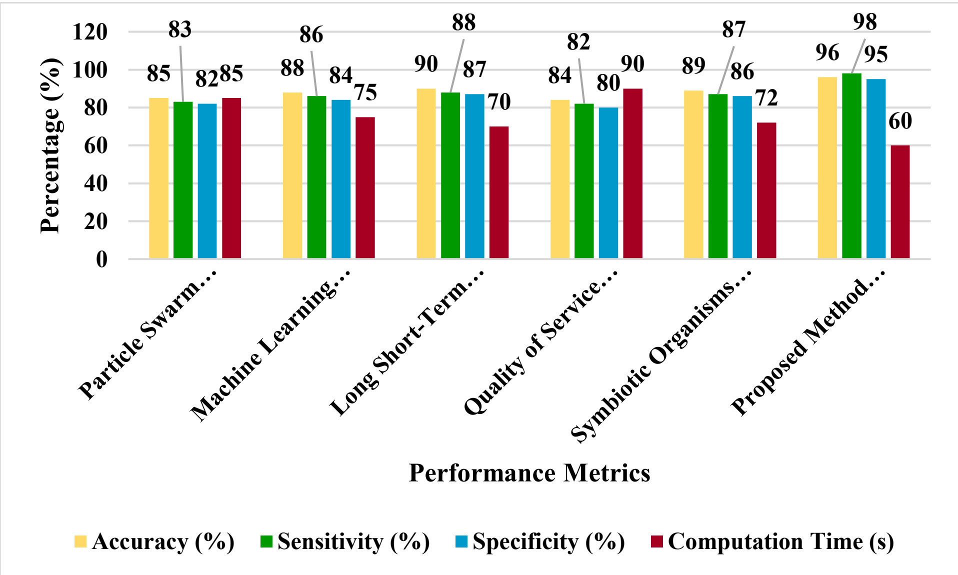

Figure 3: Comparative accuracy across traditional methods and the proposed system

The accuracy attained by the suggested approach in comparison to more conventional models such as PSO, ML, and LSTM is depicted in this figure 3. It emphasizes the way well BBO-FLC and ABC-ANFIS function, reaching 96% accuracy.

Table 3: Individual and combined performance of BBO-FLC and ABC-ANFIS

Configuration	**BBO-FLC**	**ABC-ANFIS**	**Combined (BBO-FLC + ABC-ANFIS)**
Accuracy (%)	90	93	96
Sensitivity (%)	92	95	98
Specificity (%)	88	91	95
Computation Time (s)	65	62	60

The individual contributions of ABC-ANFIS and BBO-FLC to the overall system performance are assessed in the table 3. Although each technique works well on its own, when combined, they produce the finest outcomes across the board. The combined method reduces computation time (60 seconds) while improving accuracy (96%), sensitivity (98%), and specificity (95%). This collaboration shows how combining the dynamic fuzzy rule optimization of BBO-FLC with the feature extraction and classification capabilities of ABC-ANFIS results in a more reliable and effective healthcare prediction system.

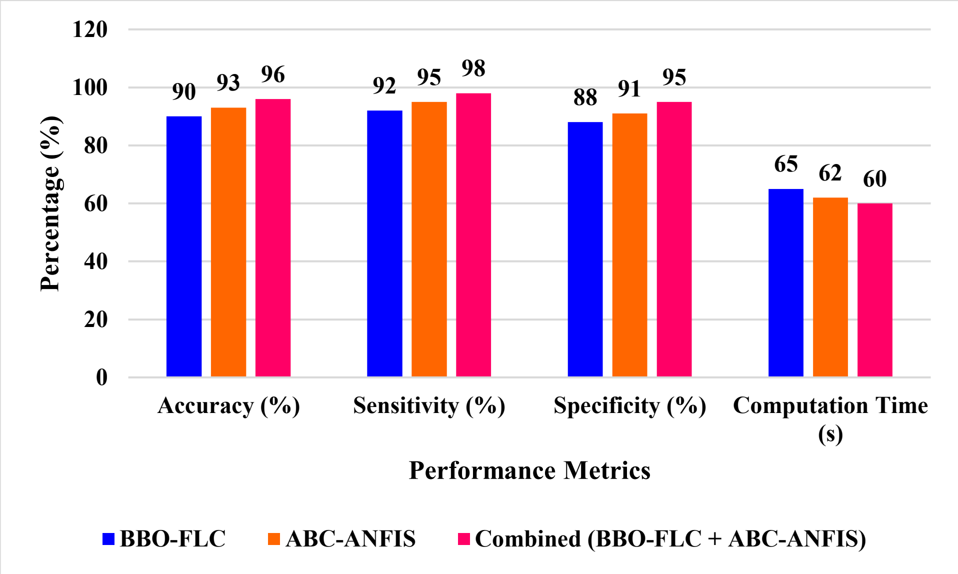

Figure 4: Effect of combining BBO-FLC and ABC-ANFIS

Combining BBO-FLC and ABC-ANFIS reduces computation time (60 seconds) while increasing accuracy (96%), sensitivity (98%), and specificity (95%), as seen in the ablation study figure 4.

5 CONCLUSION AND FUTURE SCOPE

Disease prediction and monitoring have been transformed by the integration of BBO-FLC and ABC-ANFIS in a scalable cloud architecture, and overcomes the drawbacks of conventional techniques. This approach offers a reliable and timely healthcare solution with high accuracy (96%), sensitivity (98%), and specificity (95%). Effective disease categorization and tailored therapies are guaranteed by its dynamic adaptability, while scalability is improved by the shorter computing time. As a crucial development in intelligent medical systems, the suggested framework not only increases diagnostic reliability but also optimizes healthcare workflows. This strategy can greatly improve healthcare around the world by encouraging proactive, patient-centered care delivery.

To improve real-time prediction latency, the suggested system can be further improved by adding edge computing and sophisticated deep learning models. Enhancing the system's predictive power can be achieved by adding multi-modal data, such as environmental, imaging, and genomic information. Global privacy standards compliance and data security can be enhanced through integration with blockchain technology. Further research into simulating disease evolution using generative AI models may also help us comprehend complex situations. By filling up the gaps in accessibility and individualized care delivery, this system's scalability makes it appropriate for widespread deployment in smart cities and rural healthcare.

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