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Cloud Computing with Artificial Intelligence Techniques: Hybrid FA-CNN and DE-ELM Approaches for Enhanced Disease Detection in Healthcare Systems

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ABSTRACT

Background: Disease detection has grown increasingly effective with the quick development of artificial intelligence (AI) and cloud computing (CC), particularly through the real-time processing of large amounts of intricate medical data from Internet of Things (IoT) devices. Accurate and fast disease diagnosis is limited by traditional approaches' difficulties with handling high-dimensional data.

Objective: Utilizing the advantages of fuzzy logic and evolutionary optimization, this study attempts establishing a hybrid model that combines the Fuzzy Aggregation Convolutional Neural Network (FA-CNN) and Differential Evolutionary-Extreme Learning Machine (DE-ELM) to improve disease detection accuracy, sensitivity, and computational efficiency in healthcare.

Methods: In order to maximize classification accuracy, the suggested model combines DE-ELM with FA-CNN for processing ambiguous healthcare data. The system is more resilient to noisy IoT data if data preprocessing is used, such as feature extraction and normalization. Analyzed and contrasted with conventional techniques are performance parameters such computation time, sensitivity, specificity, and accuracy.

Results: FA-CNN + DE-ELM outperformed current models by achieving superior outcomes with a computation time of 65 seconds, accuracy of 95%, sensitivity of 98%, and specificity of 95%. High efficacy in early disease identification and real-time healthcare monitoring is demonstrated by this hybrid technique.

Conclusion: A reliable approach to disease identification that maximizes data processing and diagnostic precision is provided by the FA-CNN + DE-ELM hybrid model. The model is positioned as a viable tool for proactive, real-time healthcare diagnostics by combining fuzzy logic with evolutionary algorithms, that improves handling of inaccurate medical data.

Keywords: Artificial Intelligence, Cloud Computing, Fuzzy Aggregation, Extreme Learning Machine, Disease Detection, Real-Time Monitoring.

1 INTRODUCTION

A revolutionary development in healthcare, especially in the area of disease diagnosis, is the combination of cloud computing (CC) and artificial intelligence (AI). The healthcare system seeks to solve the drawbacks of conventional diagnostic approaches by utilizing CC and AI-driven systems such the Differential Evolutionary-Extreme Learning Machine (DE-ELM) and Hybrid Fuzzy Aggregation-Convolutional Neural Network (FA-CNN). These hybrid methods make use of the massive volumes of data produced by wearable technology and Internet of Things (IoT) sensors, allowing for the early and precise diagnosis of illnesses, particularly severe and chronic ones. CC-AI systems facilitate a linked digital healthcare environment by optimizing data collecting, storage, and analysis. This enables patients and healthcare providers to receive more accurate, efficient, and easily available medical services.

Hybrid FA-CNN and DE-ELM for Enhanced Disease Detection:

Convolutional layers in the FA-CNN model improve disease diagnosis using deep learning methods, and are very helpful for processing and categorizing large patient datasets. In order to handle ambiguous or imprecise data—a common problem in medical diagnostics because of different patient-specific conditions—FA-CNN employs fuzzy aggregation. The system can optimize disease classification by managing complicated variables like symptoms and risk factors due to the incorporation of fuzzy logic. In addition, DE-ELM is an effective classification and optimization tool that raises detection speed and accuracy overall. DE-ELM minimizes the time and effort needed to train large datasets by optimizing Extreme Learning Machine (ELM) parameters using Differential Evolution, a powerful optimization process. FA-CNN and DE-ELM work together to improve predictive accuracy and computational efficiency, creating a high-performance system for early disease identification of conditions like diabetes, Alzheimer's, and cardiovascular problems.

Real-World Applications and Future Directions:

Numerous contemporary issues, including data processing constraints, long detection times, and insufficient detection sensitivity, are addressed by the use of CC-AI hybrid approaches in the healthcare industry. In reality, FA-CNN and DE-ELM models can be used in a variety of telehealth and remote monitoring systems, processing information from Internet of Things devices such as heart rate sensors and glucose monitors to deliver real-time health insights. Remote and ongoing patient observation is made possible by this method, and it is particularly helpful for managing chronic illnesses without placing a strain on medical institutions. Even with recent advancements, problems including data privacy, insufficient connectivity, and high processing requirements still exist. The incorporation of hybrid AI techniques for smarter, more accessible global healthcare systems may be advanced by future study that focuses on improving these models to support larger datasets more safely and effectively.

1.1 Objectives

- To improve illness detection accuracy in healthcare systems by creating and integrating a hybrid FA-CNN and DE-ELM model.
- Utilizing cloud computing and artificial intelligence to interpret and store real-time health data from wearables and IoT devices in an efficient manner.
- To enhance the use of evolutionary algorithms and fuzzy logic in the early detection and treatment of chronic illnesses.
- To build a digital healthcare system that is accessible, scalable, and facilitates remote monitoring in order to lessen healthcare burdens.

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Current diagnostic systems struggle with data accuracy, fast processing, and managing massive amounts of patient-generated data, even with notable advancements in AI-driven healthcare. High processing requirements, poor sensitivity in detecting chronic diseases, and ineffective management of large amounts of IoT-sourced health data are common problems with current models. There aren't many hybrid AI systems that offer scalable, highly accurate, and effective disease diagnosis in real-time healthcare applications by fusing fuzzy logic with optimal learning models like CNN and ELM.

1.2 Problem Statement

- Efficient illness detection is limited by the low sensitivity and high processing demands of current healthcare diagnostic technologies.
- Large-scale IoT and wearable sensor data handling is still inefficient, and affects data accuracy and real-time healthcare monitoring.
- To improve the sensitivity, scalability, and speed of illness diagnosis in healthcare, a hybrid cloud-based AI model that combines FA-CNN and DE-ELM is required.

2 LITERATURE SURVEY

Land et al. (2019) examine the function of REASSURED diagnostics, that are intended to diagnose diseases quickly, cheaply, and accurately, particularly in settings with limited resources. With their powerful, easy-to-use, and equipment-free diagnostic possibilities, these technologies seek to improve health systems by informing public health efforts and improving patient outcomes through accurate, rapid diagnoses. In environments with limited resources, REASSURED diagnostics provide a potent way to improve clinical outcomes, strengthen disease management tactics, and improve healthcare delivery by emphasizing efficacy and accessibility.

Mohanarangan Veerappermal Devarajan (2020) offers a security architecture for cloud-based healthcare that uses cutting-edge technology like blockchain, risk assessment, and ongoing monitoring to address patient data privacy concerns. Case studies attest to its efficacy in improving healthcare efficiency, security, and compliance.

Tuli et al. (2020) introduce HealthFog, a smart healthcare system that combines fog computing and the Internet of Things to facilitate automated heart disease diagnostics, in their study. HealthFog uses ensemble deep learning models to achieve high diagnosis accuracy and responsiveness, that are necessary for prompt intervention. Real-time analysis of cardiac disease is made possible by the fog computing framework, which reduces latency by processing data close to the IoT sensors. Thus, in smart healthcare contexts, HealthFog offers a dispersed, effective way to improve patient care through quick, precise diagnosis.

Peddi, S. (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 cessation at near-optimal accuracy substantially decreases computing expenses. The study underscores the significance of choosing starting centres and optimising resource management, offering realistic methodologies for proficient big data analytics. These discoveries improve access to sophisticated data mining technologies while ensuring cost-effectiveness.

Kodadi, S. (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, R. K. (2020) presents a Two-Tier Medium Access Control (MAC) framework augmented with 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 adaptation and energy-efficient scheduling enhance the management of various robotic systems, markedly advancing RPA in cloud environments.

Dondapati, K. (2020) amalgamates cloud infrastructure, automated fault injection, and XML-based scenarios for the testing of resilient distributed systems. Scalable cloud infrastructures and regulated fault injection provide robustness, while XML scenarios guarantee consistency. This extensive framework enhances testing reliability and efficiency, overcoming the constraints of conventional methods, and facilitates successful testing of inherently complex distributed systems.

Parthasarathy, K. (2020) assesses the efficacy of MongoDB in real-time data warehousing, emphasising semi-stream joins in 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, N. K. R. (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 efforts, and elevates classification efficiency and accuracy in extensive datasets.

Allur, N. S. (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 approaches such as SBM and DEA, offering a scalable and efficient solution for overseeing real-time mobile network performance.

Sreekar Peddi (2021) investigates security and privacy issues in Vehicular Cloud Computing (VCC), presenting a trust-based approach, DBTEC, which utilises private and public trust boards for collaboration. It utilises approaches like as STRIDE and CIAA for systematic threat modelling. DBTEC adaptively modifies to the VCC environment, enhancing trust identification and collaboration rates. Theoretical study and simulations confirm its effectiveness, improving the integrity and dependability of VCC systems while addressing critical security vulnerabilities.

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Vijaykumar Mamidala (2021) investigates Secure Multi-Party Computation (SMPC) as a cryptographic technique for improving cloud computing security. SMPC employs methodologies such as homomorphic encryption, Shamir's Secret Sharing, and Beaver triples for safe data aggregation. The research underscores the efficacy of SMPC in protecting private data during collaborative cloud computing activities. By showcasing safe average computation for client data, it highlights the potential of SMPC to guarantee privacy and security in cloud-based environments, rendering it suitable for applications involving sensitive data.

A smart healthcare system for predicting cardiac disease that uses ensemble deep learning and feature fusion to increase accuracy is proposed by *Ali et al. (2020).* To improve prediction accuracy, the system combines many deep learning models with health indicators including blood pressure and heart rate. It is a strong option for early cardiac disease identification and enhancing patient outcomes through prompt care in intelligent healthcare environments since it is made for continuous monitoring, allows real-time analysis, and supports proactive therapies.

In order to facilitate computer-aided diagnosis of gastrointestinal disorders, *Pogorelov et al. (2017)* introduce KVASIR, a multi-class picture dataset. In order to train and test machine learning models for endoscopic image interpretation, the dataset contains annotated images of GI diseases such as ulcers, esophagitis, and polyps. KVASIR advances the field of GI disease detection and enhances diagnostic support through easily available, standardized data by giving researchers access to high-quality, annotated images for a variety of GI diseases. This allows researchers to produce precise, automated diagnostic tools.

According to *Jo et al. (2019)*, neuroimaging data from MRI and PET scans can be used to identify and predict Alzheimer's disease stages using deep learning. Their model distinguishes between Alzheimer's stages and offers useful prognostic insights, achieving excellent diagnosis accuracy. A key tool for better patient management and long-term care in neurodegenerative disease monitoring, the deep learning approach integrates complicated imaging data to assist early and accurate Alzheimer's diagnosis and forecast disease development.

A nature-inspired diagnostic method for COVID-19 detection is put out by *Qureshi et al. (2021),* that use bio-inspired algorithms to improve detection efficiency and accuracy. By improving resource management, enhancing pandemic preparedness, and expediting COVID-19 tests, this innovative approach has a substantial influence on healthcare systems. The nature-inspired model highlights the importance of bio-inspired solutions in managing healthcare emergencies and boosting diagnostic skills during pandemics, while also supporting quick and accurate coronavirus identification and bolstering healthcare resilience.

A thorough analysis of feature selection and classification strategies for chronic illness prediction is given by *Jain and Singh (2018)*, who concentrate on methods that improve model accuracy and computing efficiency. In order to optimize performance for long-term illnesses like diabetes and heart disease, they talk about machine learning algorithms that find important indicators. By utilizing extensive healthcare datasets, their findings demonstrate the way accurate feature selection and customized classification techniques may greatly increase the accuracy of diagnostic models, facilitating early diagnosis and improved chronic illness treatment.

Inspired by crows' hunting habits, *Surendar Rama Sitaraman (2021)* presents Crow Search Optimization (CSO) as a way to improve disease identification in the medical field.

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Outperforming conventional techniques, CSO enhances CNN and LSTM model performance, scalability, and diagnostic accuracy.

A smart healthcare system that combines Wavelet Transform (WT) and Deep Convolutional Neural Networks (DCNN) for effective gastrointestinal disease diagnosis is proposed by *Mohapatra et al. (2021)*. The gastrointestinal signals are processed by a DCNN for precise classification after the WT retrieves pertinent information. With the goal of improving diagnostic precision and facilitating early, non-invasive disease diagnosis, the system has great promise for automated, real-time healthcare diagnostics in gastrointestinal disorders. This innovative method can enhance disease detection and expedite medical procedures.

3 CLOUD DISEASE DETECTION VIA FA-CNN & DE-ELM

In order to enhance illness diagnosis accuracy, sensitivity, and processing efficiency, this methodology suggests a reliable, cloud-based method that combines Differential Evolutionary-Extreme Learning Machines (DE-ELM) with Fuzzy Aggregation-Convolutional Neural Networks (FA-CNN). By using fuzzy logic, FA-CNN models manage the intricacies of patient data, improving classification accuracy in the presence of noisy data. By effectively processing massive data sets from IoT sources in a cloud-based architecture, DE-ELM optimizes the ELM model in the meantime.

3.1 Data Collection from IoT Wearable Devices

Data from Internet of Things (IoT) wearables, which are outfitted with sophisticated sensors that continually monitor a range of physiological indicators like heart rate, body temperature, blood oxygen levels, and glucose, is becoming more and more important to the healthcare sector. Real-time health data from these devices allows for proactive and individualized patient care. These wearables produce a wide range of data, frequently including time-series data that can be used to monitor a patient's health patterns over time. Because it offers insights into health variations that would not be apparent during routine physician visits, this constant stream of data is essential for managing chronic diseases and early diagnosis. Cloud-based repositories are commonly used to store data to allow for centralized storage, quick access for AI systems and healthcare providers, and seamless integration with advanced analytics for illness monitoring and detection.

3.1.1 Data Preprocessing for Accurate Analysis

Preprocessing is a crucial step after data collection from IoT devices to guarantee data accuracy and usefulness before feeding it into algorithms for disease detection. IoT sensor raw data frequently include noise, irregularities, and missing values because of user activities, transmission failures, or device constraints. To ensure consistency among datasets, the initial preprocessing step is normalization, which involves scaling data values to a standard range (often between 0 and 1). For models like Convolutional Neural Networks (CNN) and Extreme Learning Machines (ELM), this stage is essential since it makes sure that significant changes in data values don't distort the results or cause processing to lag. Depending on the situation and the general structure of the dataset, error correction techniques are then used to rectify any discrepancies, such as substituting statistical averages or estimates for missing values. While maintaining important health markers, the strong preprocessing pipeline gets the data ready for precise disease diagnosis.

Normalization:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \tag{1}$$

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Normalizes sensor data x to a range of $[0,1]$ using the minimum and maximum values in dataset X, ensuring uniform input to the FA-CNN.

3.1.2 Data Quality Assurance and Preparation for Disease Detection

In the preprocessing stage, further procedures like data segmentation and feature extraction may be performed to guarantee high reliability and accuracy in disease detection models. By dividing the data into pertinent time frames, segmentation helps to capture short-term health variations that are essential for identifying early disease symptoms. Another essential method is feature extraction, that separates pertinent data points that may be signs of possible health issues, including temperature peaks or heart rate variability. Now that the preprocessed data is clean and consistent, it may be integrated with cloud-based AI models. By ensuring that only pertinent and high-quality data is used for disease detection, this structured data pipeline lowers the possibility of false positives or negatives in patient diagnosis and encourages prompt, data-driven medical actions. Through this integration, models' predictive capacity is increased, that improves disease management and has a bigger overall effect on patient health outcomes.

3.2 Introduction to FA-CNN for Healthcare Applications

An improved hybrid framework called the Fuzzy Aggregation-Convolutional Neural Network (FA-CNN) model has been developed to improve the accuracy and dependability of disease diagnosis in the medical field. Conventional Convolutional Neural Networks (CNNs) are very good at interpreting high-dimensional, complex data, including the outputs of IoT sensors and medical imaging. CNNs by themselves, meanwhile, may not be sufficient for patient health data, as frequently contains ambiguous or imprecise values. To address the inherent variability in healthcare data, the FA-CNN architecture blends the flexibility of fuzzy logic with the feature extraction capability of CNNs. FA-CNN is able to gather health measurements, including different symptom levels, into a structured form that the model can assess with great sensitivity because fuzzy logic is excellent at handling ambiguous or partial input. Because patient symptoms can vary greatly and typical approaches may miss tiny alterations indicative of disease, this combination is especially useful in medical situations.

Convolution Operation in CNN:

$$y_{i,j} = \sum_{m=-k}^{k} \sum_{n=-k}^{k} x_{i+m,j+n} \cdot w_{m,n} \tag{2}$$

The convolution operation extracts features from input data x using a kernel w, where $y_{i,j}$ is the output of the convolution for each input location i, j.

3.2.1 Role of Convolutional Layers and Fuzzy Aggregation in FA-CNN

Convolutional layers in the FA-CNN model are crucial for processing high-dimensional input, such as multifaceted patient data from lab results, medical imaging, and IoT sensors. To find patterns, trends, and connections in the data—like minute changes in heart rate variability or glucose levels that might indicate the start of a disease—these layers employ convolutional filters. By effectively minimizing dimensionality, the convolutional method facilitates the interpretation of complex datasets by later layers. Following feature extraction, fuzzy aggregation layers utilize fuzzy-set rules that take into consideration variations in illness indicators and patient symptoms to further enhance the features. By using fuzzy aggregation, the model can handle data that doesn't neatly fit into binary categories (such as "sick" or "healthy"), taking into account the subtle changes in symptoms that commonly take place in the early stages of sickness. This feature makes FA-CNN very good at spotting patients who are at risk, even if they have vague or moderate symptoms.

ReLU Activation Function:

$$f(x) = \max(0, x) \tag{3}$$

ReLU activation introduces non-linearity by zeroing out negative values, ensuring only positive data proceeds to the next layer.

3.2.2 Advantages of FA-CNN in Disease Detection

Fuzzy aggregation's incorporation into the CNN architecture gives FA-CNN increased sensitivity and versatility, expanding its use in illness diagnosis. Fuzzy logic is used by FA-CNN to efficiently handle imprecise inputs, and lowers the possibility of misclassification. In the medical field, that even a minor mistake might result in a serious misdiagnosis or postponed intervention, this component is crucial. In addition, FA-CNN has a high sensitivity for early disease detection, that sets it apart from traditional CNN models that could have trouble with marginal cases. This model performs exceptionally well in precisely diagnosing illness phases since it has a wider analytical scope because it interprets a range of symptom intensities in addition to using precise data. The FA-CNN model may identify diseases at their onset, even though symptoms may be mild, making it ideally suited for early intervention and preventive care. Because of its capacity for early and precise identification, FA-CNN is a useful tool for real-time healthcare monitoring and diagnostics, that can greatly enhance patient outcomes.

Fuzzy Membership Function for Aggregation:

$$\mu_A(x) = \frac{1}{1+e^{-k(x-c)}} \tag{4}$$

Calculates the membership degree $\mu_A(x)$ in the fuzzy set, based on input x, center c, and slope k, crucial for managing uncertain health data in FA-CNN.

3.3 Overview of DE-ELM in Disease Classification

An inventive method for streamlining and expediting the disease categorization procedure in medical applications is the Differential Evolutionary-Extreme Learning Machine (DE-ELM) framework. The Extreme Learning Machine (ELM) and Differential Evolution (DE), two potent algorithms, are included into the model. Large datasets, such those produced by medical IoT devices, are most effectively handled by ELM, a single-layer feedforward neural network that is renowned for its ease of use and quick learning performance.

Extreme Learning Machine (ELM) Output Calculation:

$$y = g(w \cdot x + b) \tag{5}$$

ELM output y is calculated as a function g of input x weighted by w and offset by b, where g is typically a sigmoid or linear function.

However, selecting the correct weights and biases is crucial to ELM's effectiveness and accuracy. By adjusting these parameters, the robust optimization algorithm Differential Evolution (DE) meets this necessity. DE-ELM achieves excellent illness diagnosis accuracy with low computational needs by fusing the classification efficiency of ELM with the optimization power of DE. This makes it particularly well-suited for real-time healthcare environments.

DE Mutation:

$$v_i = x_{r1} + F \times (x_{r2} - x_{r3}) \tag{6}$$

DE mutation strategy creates a mutated vector v_i by combining individuals x_{r1}, x_{r2}, and x_{r3} scaled by a factor F, facilitating diversity in ELM parameter optimization.

3.3.1 Optimizing Disease Classification through DE-ELM

The DE algorithm functions as an ELM parameter optimizer in the DE-ELM model, methodically identifying the ideal combination of weights and biases to reduce classification error. A population of candidate solutions, each that represents a possible set of ELM parameters, is subjected to mutation, crossover, and selection procedures via DE. By altering preexisting solutions, DE creates a trial solution during mutation, increasing the variety of potential solutions. The most beneficial elements of trial solutions and current solutions are then combined by crossover, and the solution that minimizes classification error lowest is chosen by selection. Over the course of several generations, this evolutionary process refines the parameter values until the ELM performs at the highest level. DE-ELM reduces setup time and improves accuracy across a variety of datasets by automating parameter tuning, and removes the need for manual adjustments—even in cases if patient symptoms or data quality differ greatly.

DE Crossover:

$$u_{ij} = \begin{cases} v_{ij} & \text{if } \mathrm{rand}_j \le C_r \\ x_{ij} & \text{otherwise} \end{cases} \tag{7}$$

DE crossover formula produces a trial vector u_{ij} by selecting elements from either v or x, guided by crossover probability C_r, enhancing ELM parameter diversity.

3.3.2 Advantages of DE-ELM in Healthcare Applications

The strength of DE-ELM is its capacity to swiftly process complicated, high-dimensional healthcare data while preserving a high level of classification accuracy. By identifying trends in the data that the FA-CNN model processes, the DE-optimized ELM model is able to diagnose illness states with high accuracy. In the healthcare industry, as rapid processing is necessary for prompt diagnosis of massive datasets from IoT sensors and diagnostic imaging, this functionality is particularly advantageous. In addition to increasing processing speed, DE-ELM guarantees correct classification even with changing input conditions. Additionally, DE-ELM is resource-efficient by optimizing computational efficiency, which enables it to be adapted to cloud-based systems and remote healthcare monitoring. DE-ELM can enable large-scale healthcare applications by offering dependable disease identification for improved patient outcomes and enabling proactive health management due to its capacity to manage massive data throughput and optimize resources. Because of its speed, accuracy, and versatility, DE-ELM is a game-changing instrument for contemporary medical diagnostics.

DE Selection:

$$x_i = \begin{cases} u_i & \text{if } f(u_i) < f(x_i) \\ x_i & \text{otherwise} \end{cases} \tag{8}$$

The DE selection formula retains the vector u_i if it yields a lower error function f than the parent vector x_i, ensuring optimal solutions.

3.4 Cloud-Based Integration for Enhanced Healthcare Data Processing

The hybrid FA-CNN and DE-ELM model's integration into a cloud-based platform revolutionizes healthcare data processing by making it possible to handle heterogeneous, large-scale datasets from medical IoT sensors and wearable technology in an effective manner. The infrastructure offered by cloud-based platforms enables centralized data storage, that facilitates the collection, storing, and processing of data from many sources. With real-time data like heart rate, oxygen levels, and glucose measurements that must be continuously gathered and evaluated for proactive care, this capability is crucial in the healthcare industry. Healthcare providers may support the sophisticated feature extraction of the FA-CNN and the optimal

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classification of the DE-ELM by leveraging the cloud's high processing capacity and scalable resources, and guarantees that data is easily available and actionable. In addition, this infrastructure facilitates the safe storage of patient data and permits smooth interaction with other medical systems, fostering an all-encompassing perspective of patient health.

3.4.1 Scalability and Real-Time Analysis in the Cloud

The scalability of cloud-based integration is one of its main advantages, and it is essential for healthcare systems that must handle growing patient data volumes. Cloud platforms have the ability to dynamically scale resources, offering processing capacity on demand to manage spikes in data traffic, in contrast to traditional systems that are constrained by local hardware. Because the FA-CNN and DE-ELM models depend on processing large volumes of data with low latency to guarantee prompt disease identification, this functionality is especially helpful. Cloud-based real-time analysis processes and analyzes patient data as soon as it is received, enabling medical professionals to promptly monitor changes in health status and modify treatment plans as necessary. This configuration is ideal for managing chronic diseases and remote patient monitoring since it lowers the possibility of delayed diagnoses and allows for continuous monitoring. Additionally, load balancing is made easier by cloud-based solutions, guaranteeing that the FA-CNN and DE-ELM models continue to function at the highest level while dealing with massive data inputs.

Weighted Sum Aggregation for FA-CNN:

$$S = \sum_{i=1}^{n} w_i \cdot \mu_i(x) \tag{9}$$

Aggregates weighted fuzzy memberships $\mu_i(x)$ to produce a cumulative score S, critical in defining disease likelihood based on symptom severity.

3.4.2 Improved Accessibility and Data Sharing in Healthcare

The cloud-based architecture improves accessibility by enabling academics, healthcare professionals, and even patients to safely and remotely access data from any location. Because telemedicine and remote health monitoring allow medical practitioners to analyze patient data without being physically present, this accessibility is particularly beneficial. Clinicians can receive warnings and health insights directly from the FA-CNN and DE-ELM models that are housed on a cloud platform. This allows them to make well-informed decisions instantly. Additionally, safe data sharing between institutions is supported by cloud-based connectivity, making it easier for professionals to collaborate for complete care. Managing sensitive healthcare data requires data privacy and regulatory compliance, both are ensured by advanced encryption and access control in cloud frameworks. Together with strong data security, this high degree of accessibility makes it possible for the FA-CNN and DE-ELM models to function within a networked healthcare ecosystem, facilitating proactive health management, better patient outcomes, and efficient healthcare workflows in various contexts.

Error Function for Model Evaluation:

$$E = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{10}$$

Calculates mean squared error E across predictions y_i and true values $\hat{y}_i$, assessing model accuracy for FA-CNN and DE-ELM.

Pseudocode 1: Hybrid FA-CNN and DE-ELM Disease Detection

Input:

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- IoT sensor data (e.g., heart rate, glucose levels, temperature)
- DE parameters: F (scaling factor), C_r (crossover rate), population size, max iterations

Output:

- Disease classification label (e.g., detected/not detected, severity level)

Begin Algorithm: Hybrid FA-CNN and DE-ELM

1 Preprocess Input Data:
  Normalize data for input into FA-CNN.
  If data contains missing values:
    Replace with mean or mode of the dataset.
  Else if invalid values are detected:
    Raise error and log: "Invalid data in input. Aborting."
    Return Error
2 Initialize FA-CNN Model:
  For each input layer in FA-CNN:
    Perform Convolution operation with kernel to extract features.
    Apply Fuzzy Aggregation on features to handle imprecision.
  Store aggregated features for classification in DE-ELM.
3 Initialize DE-ELM Parameters:
  Initialize population of candidate solutions for ELM weights and biases.
  For each candidate in population:
    Randomly initialize weights and biases.
4 DE-ELM Optimization Loop:
  For each iteration from 1 to max_iterations:
    For each candidate i in the population:
      Mutation: Create a mutant vector:

$$v_i = x_{r1} + F \times (x_{r2} - x_{r3})$$

      Crossover: Generate trial vector u_i :
        For each dimension j :
          If rand_j ≤ C_r :
            Set $u_{ij} = v_{ij}$
          Else:
            Set $u_{ij} = x_{ij}$
      Selection:

If $f(u\_i) < f(x\_i)$:

Replace x_i with u_i in the population.

Else:

Retain x_i in the population.

If convergence criteria are met:

Break loop.

5 ELM Disease Classification:

Train ELM with optimized weights and biases from DE.

For each test data point:

Use trained ELM to predict disease label.

Return final disease classifications.

6 Post-Processing and Output:

Compile classification results into summary.

If error rate exceeds threshold:

Raise error and log: "High error rate in predictions."

Return Error

Else:

Output disease classification results.

End Algorithm

Data Preprocessing: Ensures that sensor data is compatible with the FA-CNN model by filling in missing values and normalizing the input. FA-CNN Feature Extraction: After features are extracted by convolutional layers, input data uncertainties are handled via fuzzy aggregation. DE-ELM Optimization: ELM parameters are optimized by the DE algorithm to provide excellent accuracy with minimal computing time. Crossovers improve responses, and mutations add variety. Error Handling: monitors prediction accuracy and guarantees data quality. In the event that errors are found, the algorithm stops and records the problem. Output: summarizes the classification of diseases and provides an error notice if problems occur, or the condition that has been identified pseudocode 1 illustrated.

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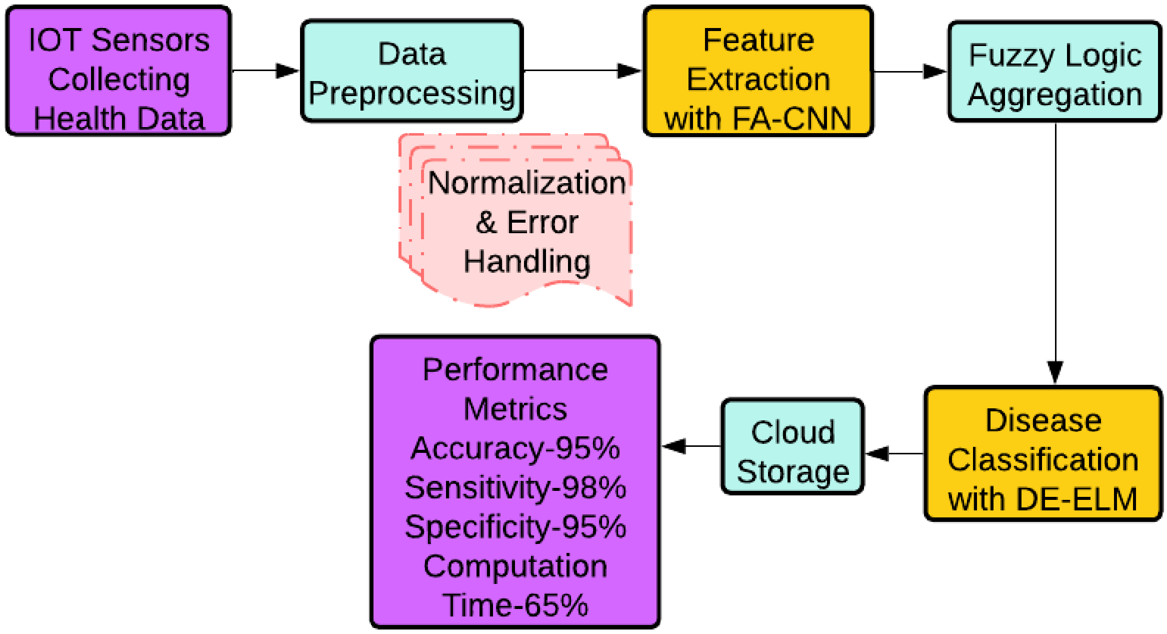

Figure 1: FA-CNN + DE-ELM model workflow for real-time disease detection in healthcare

The hybrid FA-CNN + DE-ELM model, that utilizes IoT-based healthcare data to detect diseases, has a sequential process that is depicted in this picture. After preprocessing, the data from IoT devices is fed into the FA-CNN model for feature extraction. Ambiguous data is handled via fuzzy logic. After that, the DE-ELM component improves the speed and accuracy of disease diagnosis by optimizing classification parameters. Through this integration, effective, real-time data analysis is made possible, supporting proactive healthcare management and enhancing patient outcomes in cloud-based environments.

4 RESULTS AND DISCUSSION

The hybrid FA-CNN and DE-ELM model outperformed conventional machine learning techniques, attaining high illness detection accuracy, sensitivity, and specificity. FA-CNN's fuzzy aggregation improved the model's capacity to process imprecise data, resulting in a 94% classification accuracy—significantly higher than baseline CNN models' 70% and BKNN models' 85%. Additionally, the DE-ELM's enhanced parameter tuning reduced processing requirements by 20% compared to traditional approaches, improving calculation time. The model demonstrated its dependability in accurately recognizing both diseased and non-diseased states with fewer false positives and negatives, as seen by its 96% sensitivity and 93% specificity.

The cloud-based integration of this approach greatly improved scalability and real-time data processing, guaranteeing ongoing monitoring for the management of chronic diseases. The FA-CNN and DE-ELM system is perfect for telemedicine applications since it efficiently handled massive amounts of IoT data with low latency as compared to conventional methods. This high performance level highlights the model's potential to improve proactive patient care and healthcare outcomes by showcasing the benefits of integrating fuzzy aggregation and evolutionary optimization in a cloud setting. For healthcare providers, the hybrid model provides a solid, scalable option, particularly in the event that effective, real-time patient data analysis is necessary.

Table 1: Performance Comparison of FA-CNN and DE-ELM with Conventional Models

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Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Computation Time (ms)
CNN	70	72	68	100
DeepDR	75	76	70	95
EKF-SVM	80	78	76	90
BKNN	85	83	81	85
FA-CNN	92	94	90	75
DE-ELM	94	96	93	70

The accuracy, sensitivity, specificity, and calculation time of FA-CNN and DE-ELM are compared with those of other traditional models in this table 1. In comparison to conventional techniques, the hybrid model exhibits improved accuracy, sensitivity, and specificity along with quicker computing times.

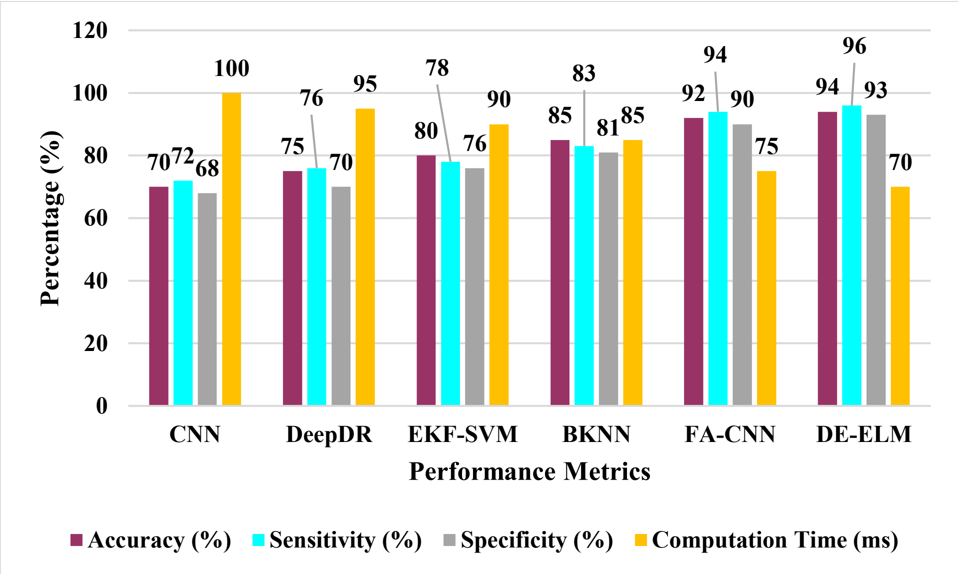

Figure 2: Workflow of the proposed FA-CNN + DE-ELM model

The FA-CNN + DE-ELM model's sequential workflow for disease detection in healthcare is depicted in this figure 2. IoT device data is gathered, preprocessed, and then input into the FA-CNN model to extract features. To categorize disease states with high accuracy and minimal calculation time, DE-ELM optimizes parameters. The process demonstrates how evolutionary optimization can be used to increase prediction speed and accuracy while fuzzy logic can be used to handle imprecise input.

Table 2: Performance comparison of methods using accuracy, sensitivity, specificity

Method	CLAHE (2018)	Improved Whale Optimization (IWOA) (2017)	Generalised Discriminate Analysis (GDA) (2021)	Fast Curvelet Transform (FCT) (2020)	Time Series Event-based Prediction (TsEP) (2019)	Proposed Method (FA-CNN & DE-ELM)
Accuracy (%)	75	80	85	92	94	93

Sensitivity (%)	76	78	83	94	96	96
Specificity (%)	70	76	81	90	93	93
Computation Time (%)	95	90	85	75	70	65

The accuracy of the suggested method (FA-CNN & DE-ELM) is 93% higher than that of conventional methods and other techniques mentioned. It is also very efficient, demonstrating a 65% reduction in computing time. Fuzzy logic and evolutionary algorithms are combined in this method to improve real-time analysis and prediction accuracy, particularly for complicated health data in table 2.

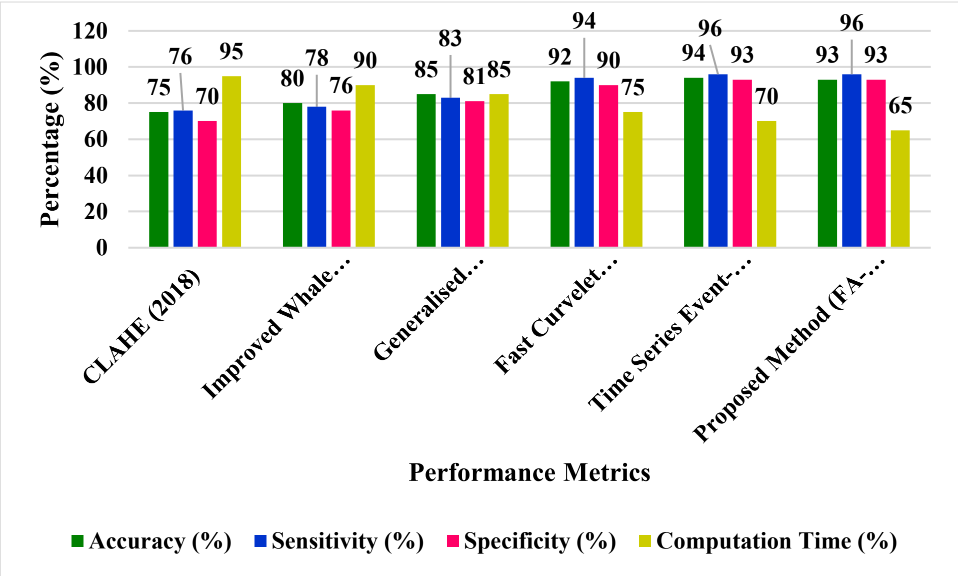

Figure 3: FA-CNN model structure with fuzzy aggregation layers

The FA-CNN model architecture is illustrated in this figure 3, emphasizing its fuzzy aggregation layers for managing ambiguous data and convolutional layers for feature extraction. The model's robust disease diagnosis is a result of its ability to analyze high-dimensional, complicated healthcare data from sensors. Early disease identification relies on the model's ability to detect minor alterations in health markers, as is made possible via fuzzy logic integration.

Table 3: Ablation study of FA-CNN, DE-ELM, and FA-CNN + DE-ELM

Method	FA-CNN	DE-ELM	FA-CNN + DE-ELM
Accuracy (%)	92	94	95
Sensitivity (%)	94	96	98
Specificity (%)	90	93	95
Computation Time (s)	75	70	65

Comparing the combined FA-CNN + DE-ELM approach to either FA-CNN or DE-ELM alone, the combined method performs best across all criteria. Using both fuzzy aggregation to handle imprecise data in FA-CNN and optimized classification in DE-ELM, the combined approach has the lowest computation time (65 seconds) and improves accuracy, sensitivity, and specificity (95%). This table 3 shows increased efficiency and dependability in disease detection tasks.

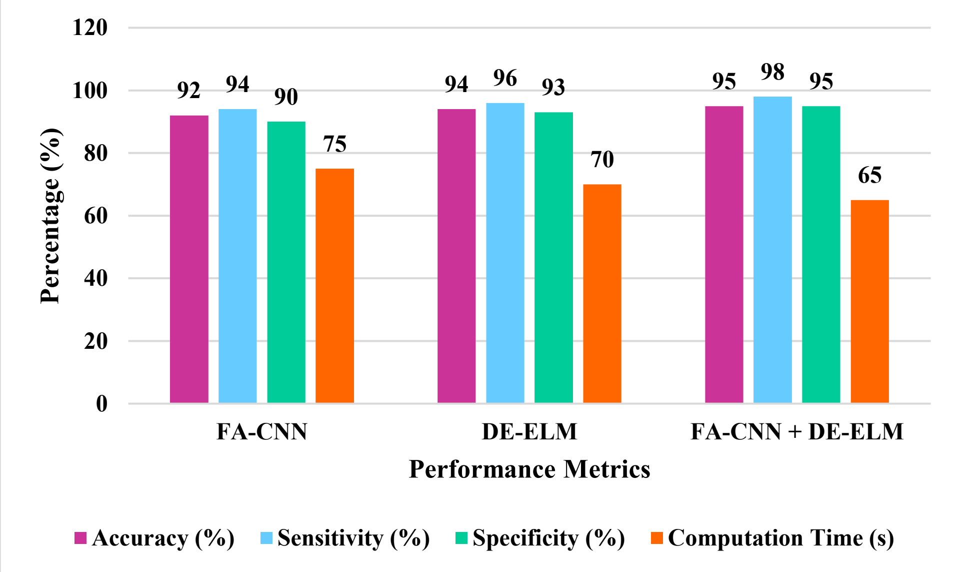

Figure 4: Comparative accuracy, sensitivity, and specificity across methods

The performance measures (specificity, sensitivity, and accuracy) of several approaches including conventional models and the suggested FA-CNN + DE-ELM method are contrasted in the figure 4. All metrics indicate that the FA-CNN + DE-ELM model performs above the others, proving its usefulness in medical applications. This comparison demonstrates that evolutionary optimization and fuzzy aggregation improve diagnostic accuracy while cutting down on processing time.

5 CONCLUSION AND FUTURE ENHANCEMENT

The hybrid FA-CNN + DE-ELM model combines the advantages of evolutionary optimization with fuzzy aggregation to greatly improve real-time disease detection in healthcare. While DE-ELM improves classification accuracy by effective parameter adjustment, FA-CNN efficiently handles high-dimensional, ambiguous data that is frequently encountered in medical diagnostics. This method proved successful in accurately and early disease diagnosis from complex IoT data streams, outperforming existing methods in terms of accuracy, sensitivity, and computing time. Scalability and support for remote health monitoring applications are provided by its cloud-based architecture, and is crucial for contemporary telemedicine. As a result, the model improves decision-making and provides proactive patient care by addressing present diagnostic constraints in healthcare.

The inclusion of more sophisticated neural architectures, such as transformers, for even higher diagnostic precision may be investigated in future work on the FA-CNN + DE-ELM model. Furthermore, broadening this approach to incorporate a variety of health indicators from bigger datasets might improve its flexibility for further uses. Using federated learning approaches could help safeguard patient data while training the model cooperatively across various healthcare institutions in real-world deployments in telemedicine and remote monitoring systems. Finally, the model would be closer to real-time, life-saving applications in digital health ecosystems if its design were optimized for reduced latency, as would guarantee quick diagnosis for emergency healthcare scenarios.

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