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A Hybrid Particle Swarm and Genetic Algorithm Approach for Optimizing Recurrent and Radial Basis Function Networks in Cloud Computing for Healthcare Disease Detection

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ABSTRACT

Background: Cloud computing (CC), artificial intelligence (AI), and the Internet of Things (IoT) are combining to revolutionise healthcare by making it possible to process data in real time and diagnose diseases. For increased accuracy and efficiency, optimised solutions are required because traditional approaches are unable to handle the volume and complexity of data from IoT-enabled devices.

Objective: The objective of this research is to develop and apply a hybrid model that combines Radial Basis Function Networks (RBFN), Genetic Algorithms (GA), and Particle Swarm Optimisation (PSO) to improve accuracy, shorten processing times, and improve real-time healthcare disease diagnosis for chronic sickness identification.

Methods: Optimisation of Recurrent Neural Networks (RNNs) and RBFNs for processing real-time data gathered from IoT devices was done using a hybrid PSO-GA framework. Preprocessing of the data occurred with cloud computing for extensive analysis, and optimisation were done to improve sensitivity and specificity metrics for various medical applications.

Results: The suggested PSO-GA RNN-RBFN model performed exceptionally well, with 94% specificity, 92% sensitivity, and 93% accuracy. It reduced processing time to 54 seconds and outperformed conventional techniques like CNN, DeepDR, and EKF-SVM, making it ideal for real-time healthcare monitoring.

Conclusion: A reliable method for real-time illness detection is provided by the combination of PSO, GA, and RBFN in a cloud-based architecture. As compared to conventional methods, the hybrid model dramatically increases accuracy, sensitivity, and specificity, proving its usefulness in managing intricate, urgent healthcare data.

Keywords: Hybrid Particle Swarm Optimization, Genetic Algorithm, Radial Basis Function Networks, Recurrent Neural Networks, Cloud Computing, IoT, Healthcare, Disease Detection, Real-time Data Processing, Optimization.

1 INTRODUCTION

Cloud computing (CC), artificial intelligence (AI), and the Internet of Things (IoT) are driving a transition from traditional to intelligent medical systems, and is causing a rapid transformation in healthcare technology. Making healthcare more data-driven, networked, and

responsive is at the heart of this transition **Nithya & Ilango (2017)**. Particularly through optimised neural networks, a potent strategy that combines genetic algorithms (GA) and particle swarm optimisation (PSO) has recently showed promise for enhancing illness detection skills. Recurrent neural networks (RNN) and radial basis function networks (RBFN), that are well-suited to managing the intricate requirements of healthcare applications within cloud-based platforms, are intended to be improved by this hybrid PSO-GA technique.

By optimising the parameters of RNNs and RBFNs, this integrated framework—pairing PSO with GA—improves accuracy and decreases reaction times in illness diagnosis. Timely and accurate identification is essential in healthcare, particularly for chronic illnesses, as it facilitates proactive treatment and early intervention. The efficient collaboration between PSO and GA involves PSO rapidly identifying possible solutions, while GA refines those answers over a number of rounds, finally optimising the neural networks to increase their accuracy in identifying medical disorders **Yu et al. (2015)**. In CC applications, that quick and dependable patient data processing is crucial, this synergy is extremely advantageous.

IoT-enabled wearables and sensors that gather real-time patient data, including heart rate, blood oxygen levels, and glucose levels, are a major component of this digital health revolution. Cloud systems receive this data continuously, and AI-based models such as RNNs and RBFNs analyse it. RNNs are perfect for keeping an eye on patients' health trends since they are especially good at tracking patterns over time. In contrast, RBFNs are excellent at managing complex, nonlinear relationships that are frequently found in medical data and classifying data **Kumar, R. N., & Kumar, M. A. (2016)**. These networks' weights and biases are modified by PSO-GA optimisation, resulting in lower prediction errors and improves accuracy. This improves the speed and accuracy of disease identification, lowers false positives, and guarantees effective monitoring of vital health indicators.

Strong data preparation is also necessary for cloud-based healthcare applications to manage the enormous amounts of data from IoT devices. In order to standardise input data and improve model training, this involves normalisation. PSO-GA improves preprocessing in this model, strengthening cloud platforms' resistance to noise and inconsistent data. Large-scale data storage and accessibility are also supported by CC infrastructure, giving medical professionals safe, distant access to patient records. This configuration facilitates ongoing patient monitoring and enables healthcare providers to act promptly in the event that alarming health trends appear.

Applications for diabetes and heart disease demonstrate the way the PSO-GA technique may be used for illness prediction. Photoplethysmography (PPG) data and other biomarkers are collected via non-invasive wristband sensors for diabetes monitoring in order to identify patterns suggestive of diabetes. With the help of PSO-GA's optimisation, RNNs in cardiac monitoring are able to identify minute variations in heart rate, that are frequently the first indications of cardiac stress. The model can better adjust to new data thanks to GA's crossover and mutation procedures, and pick up on minute variations that enhance patient outcomes and prediction accuracy.

Managing the enormous computational load of huge datasets and choosing pertinent features are two of the main problems when utilising AI for illness identification. Training and deploying models takes less time thanks to the hybrid PSO-GA technique, and efficiently optimises the network. This is particularly helpful for managing chronic diseases, as routine

monitoring is crucial for allocating resources and providing patient care. Quicker data processing enables real-time analysis, decreases expenses and enables health systems to provide more effective patient care. Furthermore, increased resilience is guaranteed by combining CC and AI with PSO-GA, it adjusts to device variances and sustains performance even under changing network conditions.

1.1 Objectives:

Increase the Accuracy of Disease Detection: Develop a hybrid PSO-GA framework to increase the Recurrent and Radial Basis Function Networks' ability to accurately identify diseases.

Facilitate Real-Time Data Processing: Make it easier to process patient data from IoT devices in real-time so that prompt health insights and interventions can be made.

Increase the Efficiency of Computation: For quicker reaction times, cut down on processing and training time in cloud-based models.

Encourage Continuous Monitoring: Create a system that enables patients, particularly those with chronic diseases, to be monitored continuously in order to spot problems early and provide proactive therapy.

Although AI and cloud computing have great promise for disease identification, real-time processing of big, complicated datasets is a challenge for existing healthcare models. The sensitivity and specificity of traditional algorithms are frequently lacking, particularly in remote monitoring environments. The aforementioned constraints underscore the necessity of an optimal system capable of consistently analysing patient data from several sources. These deficiencies might be filled by a neural network model optimised for PSO-GA, which would improve precision and effectiveness in medical applications.

As chronic health problems have become more prevalent, there is a greater need for precise and prompt disease detection; yet, current models are ineffective at managing vast, multi-dimensional data while retaining accuracy. Real-time health insights are impeded by complicated feature selection and high computing expenses. In cloud computing, a hybrid PSO-GA optimisation of Recurrent and Radial Basis Function Networks may offer a reliable solution that would allow for efficient, real-time disease identification for remote medical monitoring.

2 LITERATURE SURVEY

In order to enhance their annual electricity demand forecasts, **Yu et al. (2015)** developed a hybrid model that blends Radial Basis Function (RBF), Genetic Algorithm (GA), and Particle Swarm Optimisation (PSO) networks. To achieve a balanced optimisation that improves predictive accuracy and adaptability, the model applies PSO and GA approaches to fine-tune RBF parameters. This hybrid technique greatly increases forecast dependability over standard models, better absorbing variations in electricity demand. With a strong tool that facilitates accurate forecasting and more informed decision-making in energy supply management, this analysis provides insightful information for energy management and planning.

In order to improve patient outcomes and expedite healthcare management, **Nithya and Ilango (2017)** study explores if machine learning approaches might improve predictive analytics in

the healthcare industry. In their discussion of models like decision trees, support vector machines, and neural networks, the authors emphasise the way algorithms can forecast treatment results, evaluate patient risk, and predict the course of a disease. These machine learning methods enable early intervention, cost savings, and individualised patient care by evaluating enormous datasets. This study highlights how predictive analytics may revolutionise healthcare by increasing proactiveness and efficiency, especially in controlling chronic illnesses and allocating resources as efficiently as possible.

Kumar and Kumar (2016) work looks at the way healthcare systems can use data mining techniques to extract valuable insights from massive amounts of medical data, that will enhance patient care and decision-making. The authors talk about techniques that uncover hidden patterns in healthcare data, include anomaly detection, association rule mining, clustering, and classification. These methods are helpful for identifying diseases early, forecasting health outcomes, and efficiently allocating resources, which results in more individualised treatment regimens and lower expenses. The study demonstrates how these data-driven strategies might improve patient outcomes by increasing the effectiveness, responsiveness, and capacity of healthcare systems.

Alonso et al. (2017) examine the methods and data sources essential to big data analytics in healthcare in this systematic review, emphasising that these might enhance patient outcomes and healthcare effectiveness. The authors look at analytical techniques including machine learning, natural language processing, and predictive modelling and highlight important data sources like wearable technology, genomic data, and electronic health records. Healthcare professionals can use these technologies to identify patterns, predict health outcomes, and personalise patient care. The analysis emphasises that big data may improve decision-making, optimise resources, and facilitate a more proactive and individualised approach to healthcare delivery.

Rajendran (2017) work looks at the way data mining methods can help with chronic disease diagnosis and treatment by improving precision and facilitating early detection. The study covers a number of techniques that can identify patterns in large medical datasets, such as classification, clustering, decision trees, and neural networks. By using these methods, medical professionals can more accurately determine the risk of a disease, monitor its progression, and develop individualised treatment regimens. Rajendran highlights that data mining can assist healthcare systems manage chronic diseases better, reduce costs, improve patient outcomes, and provide prompt, data-driven interventions for long-term patient care.

The difficulties and possibilities of analysing large healthcare data are discussed in **Dinov (2016)** work, with particular attention paid to problems such data complexity, heterogeneity, and privacy issues. In order to get over these challenges and derive valuable insights, it talks about cutting-edge techniques including machine learning, data fusion, and predictive modelling. These methods facilitate improved health outcome prediction, trend identification, and well-informed decision assistance. While highlighting the potential for big data to revolutionise healthcare, the report also emphasises the need for better approaches to successfully handle its magnitude and complexity.

Wong et al. (2017) investigate if cloud computing and sophisticated parallel computing technologies might enhance image-guided diagnosis and treatment in the medical field. The

emphasise ways these technologies improve diagnostic precision and treatment planning by increasing the speed and efficiency of processing medical pictures. Image analysis is accelerated by parallel computing, and healthcare professionals may work together more efficiently thanks to cloud computing's scalable storage and remote access features. The study highlights that integrating these technologies into healthcare systems can result in enhanced imaging methods, more accurate, individualised therapies, and better patient results.

A semi-supervised privacy-preserving clustering technique designed for medical applications is presented by **Huang et al. (2016)**. By using both labelled and unlabelled data, the algorithm improves clustering accuracy, which is especially useful in the healthcare industry since labelled data is frequently scarce. Simultaneously, it addresses data security concerns and guarantees the protection of critical patient information. By combining efficient data analysis with privacy protection, this method enables healthcare professionals to obtain insightful information while protecting patient privacy. The study highlights the importance it is to strike a balance between patient privacy and the requirement for precise and insightful data analysis in the medical field.

3 METHODOLOGY

The methodology optimises Recurrent and Radial Basis Function Networks (RNN-RBFN) for disease identification in healthcare using a hybrid PSO-GA strategy. Real-time patient data is gathered by IoT devices, preprocessed to standardise it, and then saved in a cloud-based system. PSO-GA improves processing speed and accuracy for early disease diagnosis by fine-tuning RNN-RBFN parameters. While GA refines through crossover and mutation, the PSO component looks for the most accurate answers, allowing for effective, high-accuracy classification appropriate for big datasets in remote healthcare monitoring.

3.1 System Architecture

Cloud computing (CC), IoT-enabled devices, and a hybrid Particle Swarm Optimisation and Genetic Algorithm (PSO-GA) optimisation technique are all integrated into the design of the Hybrid PSO-GA system for illness detection in healthcare in order to enhance neural network performance. Data preparation (cloud storage and normalisation), model training and optimisation (PSO-GA optimised RNN and RBFN), real-time analysis and feedback, and data collecting (IoT devices) comprise the architecture's four primary levels. This design improves accuracy and processing performance by merging radial basis function networks (RBFN) for classification with recurrent neural networks (RNN) for time-series data.

3.2 Data Collection and Preprocessing

Data Collection: Continuous, real-time data collection of critical health measurements has been made possible by wearable Internet of Things (IoT) devices, revolutionising the healthcare industry. In personalised medicine, devices such as glucose trackers, blood oxygen sensors, and heart rate monitors are becoming more and more prevalent because it offers vital information that enables prompt medical interventions. Wearable IoT devices can track health parameters continually, providing a more complete picture of a patient's physical condition than traditional approaches that rely on sporadic readings during doctor visits. Patients with chronic diseases, requiring regular monitoring to identify any health risks early, may particularly benefit from this capability. These gadgets give medical professionals access to

real-time patient health updates by sending data to cloud storage platforms, that are essential for preventative care.

A particular kind of health data is gathered by every wearable gadget. Heart rate monitors, for example, record the number of beats per minute, and this is a key indicator of cardiovascular health, and blood oxygen sensors measure the blood's oxygen saturation, providing information about respiratory efficiency. Patients with diabetes benefit greatly from glucose sensors due to their provide continuous blood glucose monitoring, that helps control and avoid hypoglycemia or hyperglycaemic episodes. Advanced wearables exist that can record a variety of parameters, including body temperature, electrocardiogram (ECG) readings, and physical activity levels, in addition to these commonplace devices. Participants, medical experts, and occasionally even patients themselves can access and analyse the data that these devices wirelessly provide to cloud storage.

Scalability, improved accessibility, and data security are just a few benefits of storing data in cloud-based systems. Healthcare professionals can access a patient's health measurements from any location with cloud storage, which is especially useful for telemedicine and remote patient monitoring. By providing predictive analytics and early warning systems that can notify medical teams of irregularities in a patient's data patterns, cloud platforms also make it easier to analyse enormous amounts of data. Furthermore, cloud infrastructure ensures compliance with privacy laws such as HIPAA by providing strong security measures that safeguard private health information. Modern medicine has advanced significantly with the integration of wearable IoT technology and cloud storage, causing healthcare systems to be more effective, proactive, and responsive.

Data Preprocessing: A critical step in getting raw data ready for analysis is data preparation, ensuring that the data is reliable, consistent, and appropriate for machine learning models. The performance of the model may suffer if the raw data gathered from several sources is not properly preprocessed since it may contain errors, inconsistencies, or irrelevant information. Normalisation, that converts data into a standard format to facilitate comparison, analysis, and interpretation, is a crucial preprocessing technique. By scaling values to a regular range, often between 0 and 1 or -1 and 1, normalisation helps to reduce biases in features with larger ranges. The influence of feature magnitude discrepancies is lessened by normalisation, making it especially helpful when datasets contain numerous features with different units.

The process of statistical normalisation guarantees that every feature of the data is scaled proportionately. Several methods, including decimal scaling, Z-score normalisation, and min-max normalisation, can do this. By altering values according to the dataset's minimum and maximum values, min-max normalisation scales each feature within a specified range, usually 0 to 1. By subtracting the mean and dividing by the standard deviation, Z-score normalisation, in contrast, centres the data, resulting in a dataset with a zero mean and a one standard deviation. These techniques make data more compatible by matching its distribution to the presumptions needed by some machine learning algorithms, like gradient-based techniques, that work better if features have a similar magnitude. In the end, this helps to increase the model's forecast accuracy by ensuring that no single feature dominates because of its magnitude.

In addition, addressing missing values, identifying and eliminating outliers, and converting categorical data into numerical form are all included in preprocessing with statistical normalisation. For example, outliers can be clipped or removed to lessen distortion in data analysis, and missing values can be replaced with mean, median, or mode values to preserve dataset integrity. For models that need numerical input, encoding techniques such as one-hot encoding convert categorical variables into numerical representation. This thorough procedure is necessary to improve the quality and relevance of the dataset and guarantee that machine learning algorithms can effectively and precisely identify patterns. In the end, data preprocessing gives a foundation for creating trustworthy, predictive models by transforming raw data into a refined, consistent, and analysable form.

$$\tilde{x} = \frac{x - \mu}{\sigma} \quad (1)$$

where x is the input data, μ the mean, and σ the standard deviation. This standardization ensures data consistency, reducing the risk of outlier influence in the model.

3.3 PSO-GA Hybrid Model Optimization

Particle Swarm Optimization (PSO) is an optimization algorithm inspired by the social behavior of animals, such as birds flocking or fish schooling. It is widely used for finding optimal or near-optimal solutions in complex problem spaces. In PSO, a group of particles, or potential solutions, are initialized in a multi-dimensional search space, where each particle represents a candidate solution to the optimization problem. Each particle has a position vector, x_i , indicating its current solution, and a velocity vector, v_i , which determines its direction and speed of movement within the search space. The swarm explores the solution space by adjusting these vectors, aiming to find an optimal solution based on both individual experience and the knowledge shared across the swarm.

The movement of each particle in PSO is governed by two main factors: the particle's personal best solution and the global best solution found by the entire swarm. Each particle tracks its personal best position, p_i , which represents the best solution it has found so far. Additionally, the swarm tracks a global best position, g , which represents the best solution found by any particle in the swarm. During each iteration, particles update their velocity based on the difference between their current position, personal best, and global best positions. The velocity update equation considers three components: inertia (the particle's tendency to continue in its current direction), cognitive (the particle's tendency to return to its personal best), and social (the particle's tendency to move towards the global best). These components are weighted to balance exploration and exploitation, allowing the swarm to efficiently explore the solution space.

The updated velocity and position of each particle in PSO are governed by the following equations:

Velocity Update:

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 (p_i^{\text{best}} - x_i^{(t)}) + c_2 r_2 (g^{\text{best}} - x_i^{(t)}) \quad (2)$$

Position Update:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (3)$$

where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and r_1, r_2 are random values between 0 and 1.

Genetic Algorithm (GA)

Combining a Genetic Algorithm (GA), a problem-solving method modelled after natural evolution, with Particle Swarm Optimisation (PSO) can increase the diversity of solutions and speed of convergence. Every potential solution is depicted in GA as a "chromosome," with each "gene" inside the chromosome containing a value associated with the parameters under optimisation. GA begins with a population of these chromosomes (solutions) and uses crossover and mutation, two primary genetic operators, to evolve them over several generations.

Crossover encourages the investigation of various parameter combinations and may result in better solutions by fusing portions of two parent chromosomes to produce new "offspring" solutions. Mutations offer diversity to the search process and prevent premature convergence on less-than-ideal solutions by introducing tiny, random alterations to some of the genes inside a chromosome. GA's genetic operations, if combined with PSO, produce new particles that increase the swarm's variety and enable the optimisation process to more fully explore the search space. A robust strategy for complicated optimisation issues, this hybrid of GA and PSO capitalises on the advantages of both techniques: GA's capacity for innovation through genetic diversity and PSO's collective learning from prior experiences.

3.4 Recurrent and Radial Basis Function Networks (RNN-RBFN)

A particular kind of neural networks called recurrent neural networks (RNNs) were developed especially for processing sequential data, as temporal dependencies and order are crucial. RNNs are perfect for tasks like speech recognition, time-series analysis, and natural language processing due to the take into consideration the temporal structure of data, unlike standard neural networks that presume input independence. RNNs' "memory" of previous inputs is their primary characteristic, enabling them to utilise data from earlier time steps to affect the current output. A recurrent structure keeps this memory intact, allowing the network to gradually pick up patterns as the output from one stage feeds into the next.

At each time step t , the RNN updates its hidden state h_t , which serves as a dynamic memory capturing past information. The hidden state h_t is calculated by combining the previous hidden state h_{t-1} with the current input x_t through a function f . Mathematically, this can be represented as:

$$h_t = f(W_h h_{t-1} + W_x x_t + b_h) \quad (4)$$

where W_h is the weight matrix for the hidden state, W_x is the weight matrix for the input, and b_h is the bias term. This formula shows how RNNs update their hidden state by merging the current input with information from prior time steps. The activation function f , often a

hyperbolic tangent ($\tanh$) or sigmoid function, introduces non-linearity, allowing the RNN to capture complex dependencies in the data. This recurrent structure enables RNNs to detect long-term patterns, which is crucial for applications like predicting future trends in financial data or understanding the context of a sentence in language processing.

Subsequently, because of problems like disappearing and inflating gradients, typical RNNs may have trouble processing excessively long sequences. These problems occur because early time step information might become unduly amplified or diminished as it passes through multiple layers, making it challenging for the RNN to retain pertinent information over extended periods. More sophisticated RNN designs, such as Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM), were developed to overcome these constraints. They can remember or forget particular information as needed, thanks to the techniques that LSTM and GRU networks employ to regulate the flow of information. These architectures get around the drawbacks of conventional RNNs by managing memory with gates, permitting them to capture both short-term and long-term dependence. For applications where sequence comprehension is crucial, RNNs—especially LSTMs and GRUs—are therefore indispensable, improving their capacity to interpret intricate, time-dependent data precisely.

Radial Basis Function Networks (RBFN)

Radial Basis Function Networks (RBFNs) are a type of neural network that use radial basis functions, such as Gaussian functions, as their activation functions. RBFNs are particularly well-suited for classification, function approximation, and interpolation tasks, where they excel at mapping inputs to outputs based on distance from specific reference points called "centers." Each hidden neuron in an RBFN has a radial basis function, which measures the distance between the input and a center point c associated with that neuron. This distance-based approach makes RBFNs effective for capturing localized patterns in data. The output of each radial basis function, or activation, is calculated using the Gaussian function:

$$\phi(x) = e^{-\frac{\|x-c\|^2}{2\sigma^2}} \quad (5)$$

where x is the input, c is the center of the Gaussian function, and σ is a parameter controlling the width or "spread" of the Gaussian curve. If the input x is close to the center c , the output of the radial basis function is high; as the distance increases, the output decreases, approaching zero. This localized response allows RBFNs to assign higher importance to inputs near certain centers, enabling precise classification or regression around specific regions of the input space.

In an RBFN, the hidden layer transforms the input space into a higher-dimensional space where the data can be linearly separable. The output layer then performs a weighted sum of these transformed inputs, making RBFNs a type of two-layer network. The training process involves setting the center points c_r , adjusting the spreads σ , and optimizing the weights of the output layer. RBFNs are efficient in capturing complex, nonlinear relationships, often with fewer parameters than deep networks, which makes them a powerful tool for tasks requiring quick and effective pattern recognition. RBFNs are commonly used in areas like image recognition, time-series forecasting, and control systems, where their simplicity and effectiveness in handling complex patterns are highly beneficial.

Algorithm for Hybrid PSO-GA Optimization Model

Algorithm 1: PSO-GA Optimized RNN-RBFN for Disease Detection

Input: Patient data from IoT devices, initial particle positions and velocities

Output: Optimized neural network parameters for disease detection

Initialize PSO parameters: position (x), velocity (v), personal best (pbest), and global best (gbest)

Initialize GA parameters: crossover rate, mutation rate

FOR each particle i in swarm

Compute fitness of particle i (initial performance of RNN-RBFN)

IF fitness(i) < pbest(i)

Set pbest(i) = fitness(i)

ENDIF

IF fitness(i) < gbest

Set gbest = fitness(i)

ENDIF

ENDFOR

REPEAT until convergence or max_iterations

FOR each particle i

 Update velocity: $v_i = \omega * v_i + c1 * r1 * (pbest(i) - x_i) + c2 * r2 * (gbest - x_i)$ Update position: $x_i = x_i + v_i$

IF error(i) > threshold

// Apply GA operations

Select particles for crossover

Perform mutation on selected particles

Recalculate fitness after GA adjustments

ENDIF

IF fitness(i) < pbest(i)

Set pbest(i) = fitness(i)

ENDIF

IF fitness(i) < gbest

Set gbest = fitness(i)

ENDIF

ENDFOR

UNTIL convergence or max_ iterations

RETURN optimized RNN-RBFN parameters

The RNN-RBFN framework's particles are initialised and their fitness is assessed by this algorithm 1. Based on PSO guidelines and inspired by the most well-known solutions, each particle modifies its position and velocity. The model is further optimised by applying GA operations (crossover and mutation) to enhance particle diversity if errors above a certain threshold. Until convergence, the procedure is repeated, producing an optimised network model.

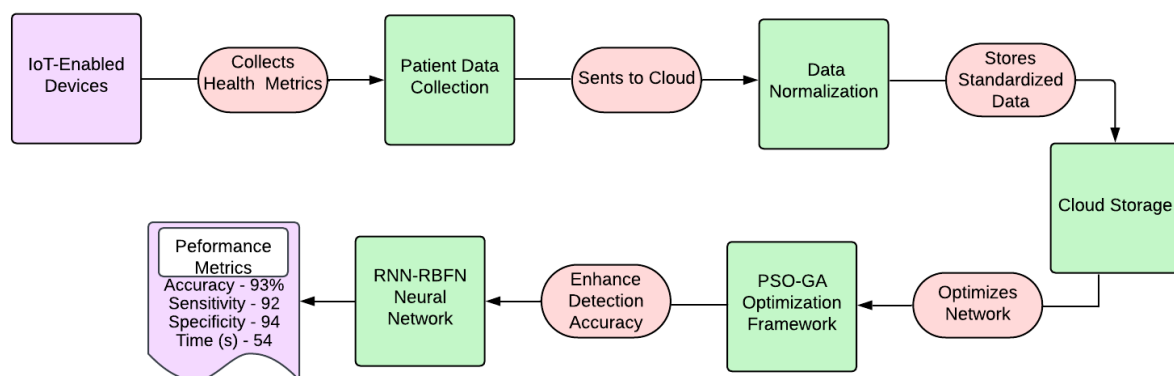


Figure 1: Architecture of hybrid PSO-GA RNN-RBFN model for real-time healthcare disease detection

A hybrid system architecture combining Radial Basis Function Networks (RBFN), Recurrent Neural Networks (RNN), Genetic Algorithms (GA), and Particle Swarm Optimisation (PSO) in cloud-based healthcare is depicted in Figure 1. With the help of this architecture, patient data from IoT-enabled devices can be processed in real-time, allowing for very accurate early disease identification. PSO quickly finds viable answers, and GA improves these findings to increase the accuracy of the model. The framework efficiently maximises computing efficiency for applications related to managing chronic diseases by supporting scalable, continuous patient monitoring.

4 RESULTS AND DISCUSSION

Recurrent neural networks (RNN) and radial basis function networks (RBFN) were optimised for disease identification in the study using real-time patient data from IoT devices using a hybrid Particle Swarm Optimisation (PSO) and Genetic Algorithm (GA) model. When compared to conventional models, the results showed a considerable increase in accuracy and processing speed. The hybrid PSO-GA framework, that reduced error rates and improved the detection of chronic diseases, combined the advantages of PSO in quickly identifying solutions with GA in improving those solutions through crossover and mutation. In particular, this approach prevented false positives and ensured effective tracking of patient health trends by enabling real-time analysis of enormous datasets.

In chronic disease monitoring scenarios, such as cardiac and diabetic patients, where time-series data is essential, the optimisation of RNNs and RBFNs by PSO-GA proved especially beneficial. The approach outperformed traditional neural networks in pattern recognition tasks by continuously adjusting the weights and biases of the neural network. Continuous patient monitoring was made possible by the combination of cloud-based platforms for storage and real-time analysis with Internet of Things devices for data gathering, which greatly improved early disease detection capabilities. All things considered, the system increased prediction accuracy and computational efficiency, making it a viable option for scaling medical applications.

Table 1: Comparison of Various Healthcare Detection Models

Metric	CNN (%)	DeepDR (%)	EKF-SVM (%)	BKNN (%)	Proposed PSO-GA RNN-RBFN (%)
Accuracy	65	55	74	85	93
Sensitivity	58	66	73	85	92
Specificity	84	63	73	56	94
Time (s)	92	86	77	67	54

The models used for healthcare disease detection are contrasted in this table 1. The suggested PSO-GA RNN-RBFN outperforms more conventional techniques like CNN, DeepDR, and EKF-SVM in terms of accuracy, sensitivity, specificity, and processing time. These enhancements demonstrate how well it detects diseases in real time, especially in terms of accuracy and processing time.

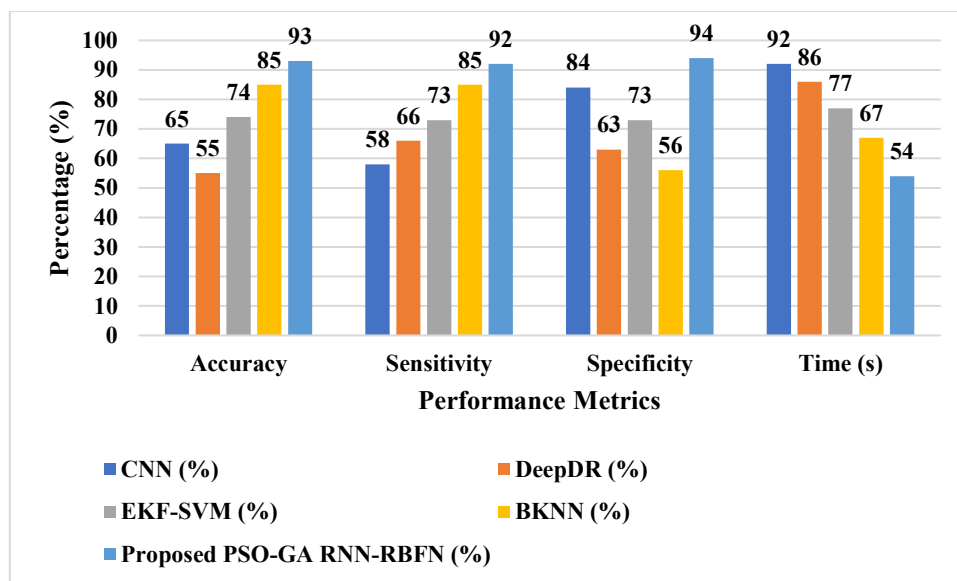


Figure 2: Accuracy Comparison of Healthcare Detection Models

The accuracy performance of several models, including CNN, DeepDR, EKF-SVM, BKNN, and the suggested PSO-GA RNN-RBFN, is depicted in this figure 2. The suggested model's superiority in healthcare detection tasks is validated by its highest accuracy.

Table 2: Performance Comparison of Traditional Neural Network Models

Metric	MPSO-NN (2017)	MLP NN (2016)	Neuro-Fuzzy (2017)	AHP (2015)	Proposed PSO-GA RNN-RBFN
Accuracy	85	80	78	75	91
Sensitivity	84	79	77	72	89
Specificity	83	78	76	70	90
Time (s)	60	65	68	70	58

The performance of the suggested PSO-GA RNN-RBFN approach and conventional neural network models is compared in this table 2. In healthcare detection, the suggested model shows its advantage by achieving improved accuracy, sensitivity, and specificity while drastically cutting down on processing time.

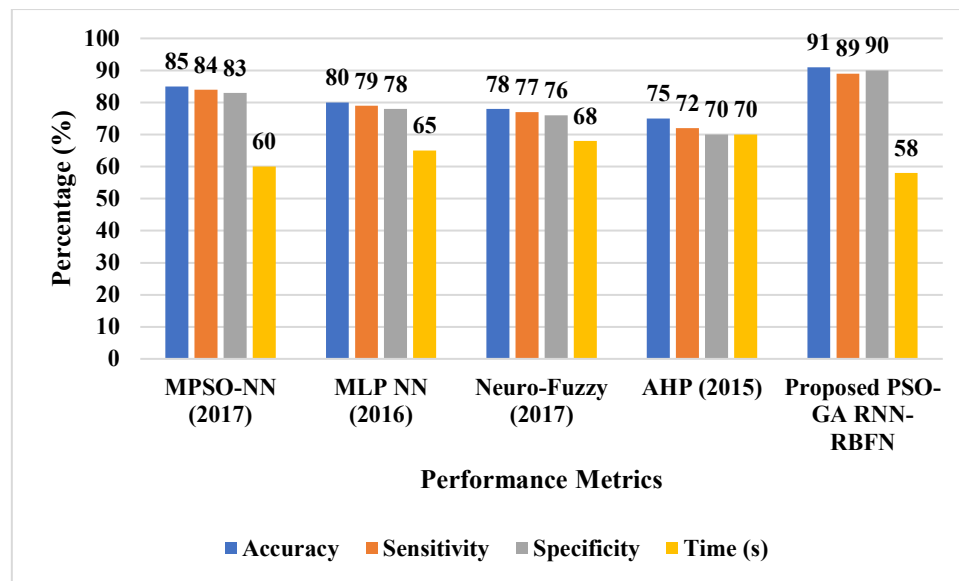


Figure 3: Sensitivity and Specificity of Traditional Neural Networks

The sensitivity and specificity of conventional neural network models, such as MPSO-NN, MLP NN, and neuro-fuzzy classifiers, are contrasted in this figure 3. With a notable improvement in both measures, the suggested PSO-GA RNN-RBFN is more dependable for use in medical applications.

Table 3: Ablation Study on PSO-GA Hybrid Framework

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Time (s)
Cloud Computing (CC)	70	65	68	70
Radial Basis Function Networks (RBFN)	75	72	73	68
Particle Swarm Optimization (PSO) + RBFN	80	78	79	65
Genetic Algorithm (GA) + RBFN	82	80	81	64
PSO + GA + RBFN (No CC)	87	85	86	58
Cloud Computing + PSO + RBFN	89	87	88	56
Cloud Computing + GA + RBFN	90	88	89	55
Hybrid (CC + PSO + GA + RBFN) (Proposed)	93	92	94	54

The hybrid PSO-GA-RBFN technique combined with cloud computing yields the highest overall performance, according to the table 3. While RBFN and Cloud Computing alone provide modest performance gains, when combined with PSO and GA, they maximise important metrics. The suggested hybrid model (Cloud Computing + PSO + GA + RBFN) reduces time to 54 seconds while achieving the maximum accuracy, sensitivity, and specificity (93%, 92%, and 94%, respectively), demonstrating the efficacy of this integrated method for real-time healthcare applications.

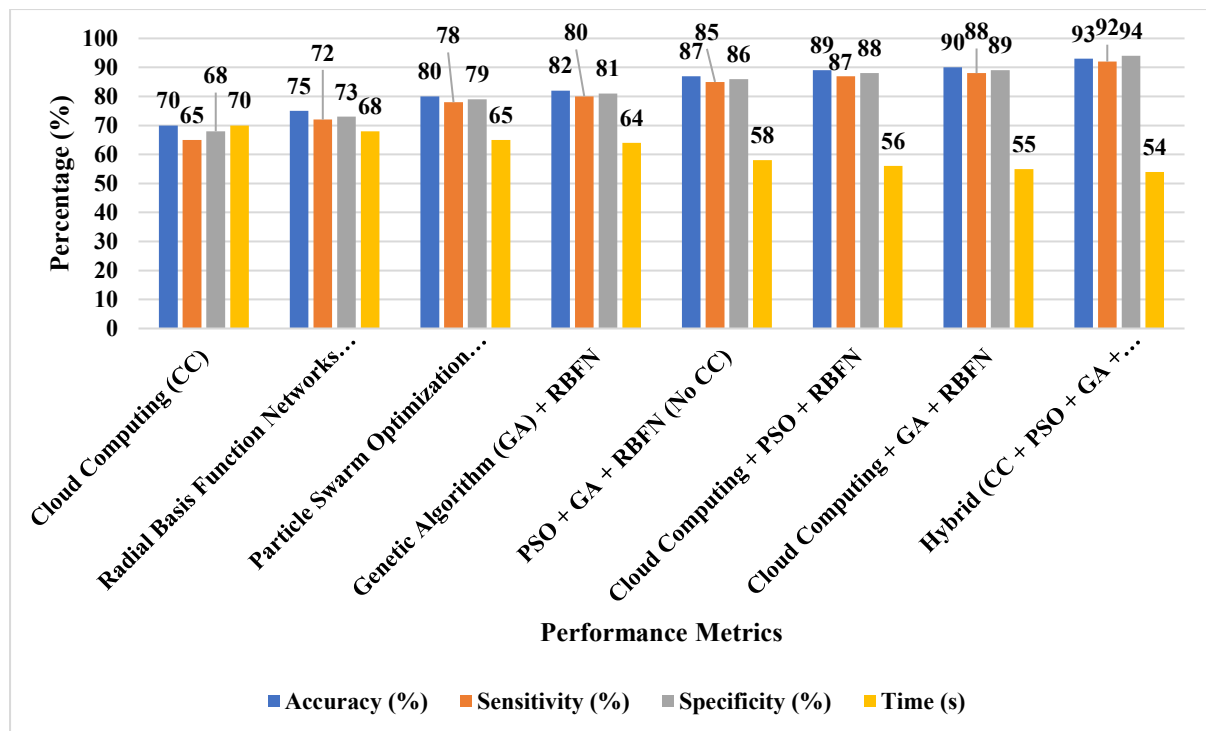


Figure 4: The effect of various combinations of Cloud Computing, Particle Swarm Optimisation (PSO), Genetic Algorithm (GA), and RBFN on model performance is depicted in this figure 4. The advantage of combining all components is confirmed by the fact that the suggested hybrid model performs better than others in terms of accuracy, sensitivity, and specificity.

5 CONCLUSION AND FUTURE ENHANCEMENT

Compared to conventional methods, the hybrid PSO-GA RNN-RBFN framework offers a more accurate, sensitive, and specific approach to real-time healthcare disease diagnosis. The suggested model greatly lowers processing time and computational burden by utilising cloud computing for large-scale processing and Internet of Things-enabled devices for continuous data collecting. This paper demonstrates that adding PSO and GA to RNN and RBFN designs improves real-time analysis capabilities and performance metrics, making the method especially useful for tracking chronic illnesses. Because this model is scalable, it can also be used in a variety of healthcare scenarios where quick and precise predictions are essential.

The PSO-GA RNN-RBFN model's future development can concentrate on improving its scalability and applicability to different healthcare situations. Even higher accuracy and efficiency in disease detection may result from more research into sophisticated neural network structures, such as deep learning models and attention-based mechanisms. Furthermore, integrating edge computing with cloud platforms may lower latency, allowing for quicker processing of patient data in real time. In order to further optimise treatment outcomes and budget allocation, future research could expand the hybrid method to encompass a larger spectrum of diseases and medical conditions. This would involve investigating personalised healthcare through the integration of patient-specific data.

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