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AI-Driven Healthcare System For Doctor Recommendation Based On Deep Vectorized Grey Wolf Optimizer With Resnet50- Convolution Neural Network

¹ S Dineshkumar, ² S Arunkumar, ³ Mr. S. Prabhu M.Tech., (Ph.D),

¹² Student, ³ Head of the Department,

Department of Artificial Intelligence and Data Science,

Paavai College of Engineering, Pachal, Namakkal,

Abstract—Artificial intelligence plays a vital role for advancing decision taken through various services especially for healthcare decisions to make analyses, solving and recommendations. Throughout healthcare data from patients are analyzed using machine learning and deep learning models. By identifying disease affected feature and related treatment for doctor recommendation is important for right progress medications. Traditional methods are failed to analyze the feature importance of relational properties to find the proper recommendation which affects due to improper data decisions leads poor accuracy from false rates. To resolve this problem, the paper proposed an AI-Driven Healthcare System for Doctor Recommendation based on deep vectorized Grey Wolf Optimizer (GWO) with Resnet50- Convolution Neural Network for identifying disease related treatment and doctor recommendation. The initially the Z score normalization is carried out to healthcare dataset to normalize the dataset with verified margins. Then disease relational impact score is analyzed using support deep vector scar function. depending on the feature impact, the mutual dependencies of feature rate is evaluated with grey wolf optimization and classification is done with Resnet50- CNN of categorize the patient dependent doctors for recommendation. The implementation result proves best precision rate up to 95.2 % high, recall up to gain 94.8 % high with f1 score 96.5 % well compared to the existing system with redundant false rate. The proposed system well suitable for disease related risk analysis and recommendation for diagnosis with specialist doctor recommendation for immediate treatment depending on the risk by class.

Keywords—Artificial Intelligence, Healthcare, Doctor Recommendation, Deep Learning, Convolutional Neural Network, Grey Wolf Optimizer, Feature Importance, Risk Analysis.

I. INTRODUCTION

The healthcare industry is entering a new age when large amounts of medical data will become increasingly crucial. Artificial intelligence (AI) is rapidly transforming numerous sectors, and its potential in healthcare is particularly promising. Specifically, AI-driven systems are emerging as vital tools for enhancing decision-making processes, offering the capability to analyze vast datasets, identify critical patterns, and provide insightful recommendations. Within this context, to patient healthcare data offers the prospect of identifying disease-affected features and suggesting appropriate treatment pathways, crucial for ensuring effective and timely medical intervention [1]. However, traditional methodologies often fall short in adequately capturing the intricate relational properties inherent in healthcare data, leading to inaccurate assessments and potentially detrimental false positive and negative rates.

For example, healthcare accuracy considers a variety of patient data, including differences in molecular characteristics, Electronic Health Records (EHRs), environment, and lifestyle. This disparity makes it more difficult to achieve the best outcomes. Since Bangladesh is a pioneer in the adoption of digital technology, closing this gap is essential to making the most of these cutting-edge tools [2].

Pandemics are often quite complex since they can begin with mild disease and then gradually spread to the respiratory system, affecting the internal immune system and eventually causing multi-organ failures in the majority of patients, followed by cardiac arrests and fatalities [3]. AI is being used in several fields, including contact tracking, medical, data analysis, clinical trials, treatment planning, transmission rates, and hotspot detection. According to experts, artificial intelligence will significantly influence the technological environment, as well as other fields. Additionally, the healthcare sector in industrialized nations produces a lot of data, which further introduces the idea of big data [4]. This promotes more proactive and preventative treatment, enabling medical service providers to resolve problems early and maybe avert more serious ones. Additionally, data analysis can give insight into population health patterns, aiding health authorities in making better educated decisions on resource distribution and disease preventive measures. Using effective data collecting and analysis techniques, this research presents a novel paradigm for early illness diagnosis in IoT-based smart healthcare systems [5].

To address these limitations, innovative approaches are being developed to leverage the power of AI for doctor recommendation systems. One such approach, as detailed in the aforementioned abstract, proposes an AI-Driven Healthcare System for Doctor Recommendation predicated on a deep vectorized Grey Wolf Optimizer (GWO) integrated with a Resnet50-Convolution Neural Network (CNN). This system aims to identify disease-related treatments and subsequently recommend suitable doctors. The methodology commences with Z-score normalization, a crucial preprocessing step that standardizes the healthcare dataset within verified margins. Subsequently, a support deep vector scar function is employed to analyze the disease relational impact score, quantifying the influence of various features. Building upon this feature impact analysis, the mutual dependencies between features are evaluated using the Grey Wolf Optimization algorithm. The culmination of this process involves classification via a Resnet50-CNN, effectively categorizing patients and aligning them with appropriate specialist doctors for recommendation.

II. RELATED WORK

An Internet of Things (IoT)-based smart medical service involves the use of networked smart devices and sensors, such as wearable's, trackers, and portable apps, to collect and transmit ongoing health data to caregivers and experts. This development focuses on reorganized care, timely reflections, remote monitoring, and clinical concerns regarding patients. [6]. To find scholarly ramifications, we used certain keywords to locate the most well-known journal and conference databases [7].

With the use of the aforementioned technologies in machine Learning like Random Forest (RF), this scoping novel seeks to (1) compile the body of research in Bangladesh's healthcare system and synthesize its

findings, and (2) identify the challenges researchers have when incorporating the a forementioned technology into healthcare research [8]. The study used QUADAS-2, most doctor recommendation system are web-based solution that we employed for data processing and extraction. [9].

An extensive survey of DNNs and their different hybridization forms is presented in this study. Retrained DNNs, hyper parameter-tuned optimal heuristic algorithms [10]. This study includes deep learning methods like LSTM, GRU, and Bi-LSTM, as well as machine learning methods including logistic regression, random forests, support vector machines, and Naïve Bayes. [11].

To promote a more open, reliable, and efficient use of AI in medical settings, this study attempts to close the gap between state-of-the-art computational approaches and their real-world use in healthcare. The findings drive industry and research, encouraging innovation and standardization in the application of XAI in healthcare [12]. The suggested Stacked DL Model produced a 93% accuracy rate, a 94% F1-score, and a 99% specificity using the MRI data that was acquired from Cagle. [13].

The author explains about fusion approaches, the illnesses and clinical results to which multimodal fusion has been applied, the machine learning algorithms such Support Vector Machine (SVM) that carry out multimodal fusion for every clinical application, and the multimodal medical datasets that are now accessible [14]. The author talks about how AI is crucial for enhancing the functionality of IoT and point-of-care (POC) devices used in cutting-edge medical fields, including diabetes treatment, cancer detection, and cardiac assessment. [15].

Most of AI models in digital twin predictive analytics prototypical cretes the data analysi based recommendation system. A smart and intelligent healthcare environment can be created, individualized therapy can be offered, and healthcare procedures may be improved by integrating digital twins [16]. This paper provides a comprehensive overview of DNNS and their several hybridization types. Five categories have been established to accomplish this: retrained DNNS, hyper parameter-tuned optimized in LSTM-Recurrent Neural Network (RNN), hybrid DNNS and ML classifiers and feature selection DNNS based on meta-heuristics [17]. Medical research, medication development, patient care, and illness diagnosis are just a few of the significant contributions this technology is making. AI systems can examine vast volumes of data and identify trends that may result in novel medical discoveries and individualized treatment plans [18].

The success of healthcare applications has been aided by the particular difficulties presented by AI, such as its availability, affordability, and accessibility. Another element that improves AI's performance is the medical data that is sourced, examined, and then used to build a model that uses machine learning (ML) to forecast the disease [19]. This study may result in the use of DL and AI for automated analysis. AI can revolutionize healthcare by enhancing productivity, accuracy, and speed; lowering costs; expanding access; decreasing errors; and changing training and education for healthcare workers [20].

III. PROPOSED METHODOLOGY

Towards development of an AI-driven healthcare system, detailed in a recent study, designed to enhance doctor recommendations by leveraging a novel combination of Deep Vectorized Grey Wolf Optimization (GWO) with a ResNet50-Convolutional Neural Network (CNN) architecture. The proposed system directly addresses this limitation by prioritizing the analysis of relational properties and feature importance, leading to more precise doctor recommendations and potentially improved patient outcomes.

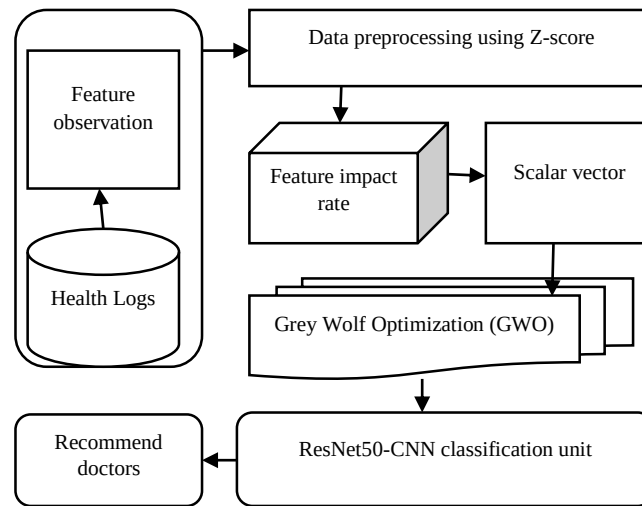


Fig. 1. Proposed GWO- ResNet50-CNN workflow architecture

The system operates through a series of meticulously orchestrated steps. Initially, the healthcare dataset undergoes Z-score normalization. Following normalization, a "deep vector scalar function" analyzes the disease relational impact score. Figure 1 shows the proposed GWO- ResNet50-CNN workflow architecture is likely refers to a function, possibly based on deep learning embeddings, that quantifies the influence of different patient characteristics on disease severity and progression, providing a more nuanced understanding of the underlying relationships.

The system then employs Grey Wolf Optimization (GWO) to evaluate the mutual dependencies between features, guided by the previously calculated impact scores. GWO, a bio-inspired optimization algorithm, excels at identifying optimal combinations of feature weights, allowing the system to prioritize the most relevant factors when making doctor recommendations. Finally, a ResNet50-CNN is utilized for classification, categorizing patients based on their specific needs and matching them with the most appropriate specialist doctors. ResNet50, a deep residual network, for identifying disease related feature patterns in high-dimensional data, ensuring accurate classification even with intricate patient profiles.

A. Data normalization

A healthcare dataset are collection of patient feature which is tested under different margins including blood samples values, scan values and observation values are represented as dataset G as feature labels and the actual and ideal margin of feature labels and its values are defined. The step evaluated the absolute margin of actual feature values verified with ideal patient margins remove the noise from the dataset.

Algorithm:

Step 1: Input From $G \leftarrow$ for $q = 1$ to U

for $x = 1$ to T

if $G(q, x)$ ideal verified from X number of actual values $G(q, x)$

Step 2: for $x = 1$ to T

Compare the actual margins with ideal ranges $G \rightarrow$ for all x

$It(x) = (\text{compute the mean value of } g)/r$

for $q = 1$ to U

for $x = 1$ to T

if $G(TxU)$ is a missing value then alternate $It(x)$ to $G(TxU)$

Step 3: for $x = 1$ to T

Find the accuracy value. It of the entire properties of the column x

$\text{Min}(x) = (\text{minimum of all the characteristics of } x)$

$\text{Max}(x) = (\text{maximum of all the characteristics of } x)$

for $q = 1$ to U

for $x = 1$ to T

if $G(U, T)$ verifies the range different union and integrate between $\text{Min}(x)$ and $\text{Max}(x)$ to $G(U, T)$

The min max- verifies all the feature margin ranges observed from patient dataset to remove the non-relevant values to reduce the feature dimension for further feature evaluation.

B. Deep vector scalar function

The Deep vector scalar function remains one of the most popular tools for classification operations, which medical data analysis, along with feature selection, heavily depends on. With its central position, Scalar impact finds the most relevant and distinct characteristics that emerge from intricate high-dimensional medical dataset collections. The construction of an optimal hyperplane defines class separation (diseased vs. healthy patients) with maximum margin, allowing SVM to find key features for accurate classification. The scaling function algorithm utilizes wrapper or embedded methods in feature selection tasks to evaluate feature subsets and their impact on final classification results. The technique demonstrates outstanding value when processing medical data, as it enables dimensional reduction by eliminating unnecessary features, resulting in improved diagnoses and operational efficiency. The kernel functions enable SVM to manage non-linear relationships, making it suitable for medical applications that require processing noisy and imbalanced data sets with non-linear boundaries.

The single patient record $\vec{x}$ representing a medical dataset appears as a vector $\vec{x} = [x_1, x_2, \dots, x_n]$, which contains medical attributes x_j (e.g., glucose level, blood pressure, age) as its components. SVM determines a patient's health status by processing these features as input. Weight assignment for each feature component of $\vec{x}$ during training occurs through the acquired vector $\vec{w} = [w_1, w_2, \dots, w_n]$. SVM utilizes the vector for assessing the significance of its features. Patients can determine the importance of medical features S through the calculation in Equation 1.

$$S_j = |w_j| \quad (1)$$

Absolute weight sizes determine the importance of individual features for classification purposes, thereby affecting their probability of selection in feature choice protocols. The parameter b functions as the decision boundary intercept, which affects its position. A bias value in the hyperplane helps achieve optimal separation between patients who are not distributed around the origin. It appears in the main decision function,

$$f(\vec{x}) = \vec{w} \cdot \vec{x} + b \quad (2)$$

This decision function $f(\vec{x})$ computes the distance of a patient's data from the separating hyperplane. According to SVM, the sample receives classification through equation 3,

$$f(\vec{x}) = \vec{w} \cdot \vec{x} + b \quad (3)$$

The training sample is classified as one category if $f(\vec{x}) > 0$, whereas $f(\vec{x}) < 0$ leads to a different classification as healthy or diseases. Each training example contains a true label y_i , which is either +1 or -1, where +1 represents diseased patients and -1 represents healthy patients. The SVM seeks to satisfy,

$$y_i = (\vec{w} \cdot \vec{x}_i + b) \geq 1 \quad (4)$$

The classification approach must correctly identify each sample by applying minimum boundaries of 1. Training sample i has its actual input vector $\vec{x}_i$, which consists of patient medical profile elements $x_{i1}, x_{i2}, \dots, x_{in}$. During optimization, $\vec{w}$ and b are determined by this parameter. Medical datasets containing patient records typically include excessive noise and data overlap as a standard procedure. Misclassifications are handled through the slack variable $\xi_i \geq 0$ in SVMs. The optimization problem becomes,

$$\min_{\vec{w}, b, \xi} \frac{1}{2} \|\vec{w}\|^2 + C \sum_{i=1}^n \xi_i \quad (5)$$

subject to:

$$y_i(\vec{w} \cdot \vec{x}_i + b) \geq 1 - \xi_i \quad (6)$$

The constant value $C > 0$ regulates the decision between achieving a larger margin and minimizing classification mistakes. Large C settings result in fewer misclassifications, improving critical medical diagnoses, while smaller C values permit more margin violations to achieve generalization. The decision function becomes,

$$f(\vec{x}) = \sum_{i=1}^n \alpha_i y_i K(\vec{x}_i, \vec{x}) + b \quad (7)$$

Equation 7 enables the model to recognize complex nonlinear patterns that exist between symptoms and their corresponding diagnoses. Each training point receives influence through the values α_i , which appear in the final decision function. The decision boundary gets defined through support vectors that belong to the training points with non-zero α_i values. Borderline medical diagnostic cases hold significant importance during the process of learning subtle decision patterns.

C. Optimal Feature selection-GWO

The Grey Wolf Optimizer (GWO) operates as a natural algorithm that replicates the behavior of grey wolves in their group leadership structure while they hunt together in their habitat. GWO enables the identification of quality features from complex, large-scale medical datasets, which are utilized in medical diagnostics and health informatics applications. The social behavior simulation of grey wolves, including alpha, beta, delta, and omega, within the algorithm enables it to efficiently explore the search space, thereby finding optimal feature subsets that enhance classification accuracy through redundancy reduction. The efficiency of machine learning models in medical data relies on relevant features, as unneeded or noisy inputs can diminish their functional ability. The balanced feature selection capabilities of GWO make it suitable for identifying useful diagnostic data features that improve medical diagnosis accuracy while optimizing data processing speed.

At iteration t , the medical dataset utilizes $\vec{X}(t)$ to display possible selected features, which consist of values representing specific medical attributes (e.g., blood pressure, glucose level, symptom indicator). Each position in $\vec{X}(t)$ contains either 0 or 1 to indicate selection or non-selection. The leader wolves' effect leads to the following calculation for the following position update,

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (8)$$

The formula demonstrates how the alpha α , beta β , and delta δ solutions lead to optimal diagnosis accuracy through feature combination guidance. These vectors represent top-performance solutions based on classifier-trained medical feature analysis, as they are ranked as the first and third selections. The classification accuracy is highest with the alpha vector ($\vec{X}_\alpha$), followed by the beta vector ($\vec{X}_\beta$) and then the delta vector ($\vec{X}_\delta$). Through equation 9, these wolves contribute to calculational positions that guide the others.

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \quad (9)$$

In this equation 9 and 10, $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ represent the leader wolves, $\vec{A}$ is the classification accuracy, and $\vec{D}_\alpha, \vec{D}_\beta, \vec{D}_\delta$ are the distance vectors. The vectors evaluate the absolute positional differences between the present solution and each leader through a random coefficient $\vec{C}$, which maintains search diversity.

$$\begin{aligned} \vec{D}_\alpha &= |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}(t)| \\ \vec{D}_\beta &= |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}(t)| \\ \vec{D}_\delta &= |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}(t)| \end{aligned} \quad (10)$$

The optimizer uses these terms to evaluate both distance from best solutions and current solution positions through the $\vec{A}$ and $\vec{C}$ mechanisms. The $\vec{A}$ and $\vec{C}$ control exploration through new feature combinations while also enabling exploitation of current excellent feature combinations. They are computed as,

$$\begin{aligned} \vec{A} &= 2a \cdot \vec{r}_1 - a \\ \vec{C} &= 2 \cdot \vec{r}_2 \end{aligned} \quad (11)$$

The decreasing parameter values from 2 to 0 are represented by a , and both vectors $\vec{r}_1, \vec{r}_2$ exist within the range $[0,1]$. During feature selection, the coefficients help adjust leader influence while ensuring a random approach to combination selection. As the parameter a decreases during execution, the algorithm transitions from global search to local search.

$$a = 2 - \frac{2t}{T} \quad (12)$$

The current iteration t corresponds to T , which stands for the maximum iteration limit. The technique enables medical data analysts to start with multiple feature sets during the first stages, followed by best subset optimization. The use of $\vec{r}_1$ and $\vec{r}_2$ random vectors ensures randomness, which helps the wolves avoid early convergence. The algorithm explores multiple feature combinations through random processes, allowing it to detect unfamiliar or difficult-to-recognize relationships within medical data that enhance prediction results. The GWO determines the quality of selected feature subsets by using the fitness function F , which combines both classification precision and reduced feature count according to Equation 13.

$$F = \alpha \cdot (1 \cdot A) + \beta \cdot \frac{|S|}{|N|} \quad (13)$$

Where A represents the classification performance using the selected variables, which are controlled by parameters α and β against $|S|$ features, while $|N|$ indicates the total number of attributes. This method is used in medical diagnostics, enabling selected features to perform well diagnostically while keeping their number low to preserve the clarity of results and maximize computational speed.

D. Classification Unit- Resnet50-Convolutional Neural Network (CNN)

This section analyzes the CNN model of neural networks with Resnet50, TAKES Medical Feature Limits weights, parameters, and biases using filters, kernels, and neurons. Each filter rotates the images in the facial image dataset as input and adds linearity. Furthermore, the CNN structure analyzes the image using a rotation layer, a pooling layer, a revised linear unit (ReLU) with Resnet50, and a fully connected layer. Convolutional layers are at the heart of convolutional networks and perform most computing tasks. It takes selected dense layer medial features with relevant medical margins into the convolution layer Resnet 50 reduce the non-related feature patterns

The convolutional layer constructs the healthcare feature set into Resnet50 layer and calculates the input image's convolution kernel as shown in Equation 14. Let's assume K –kernel, $C(i, j)$ –input convolution kernel, m, n – convolution operation

$$C(i, j) = \sum_m \sum_n I(i + m - 1, j + n - 1) K(m, n) \quad (14)$$

Block normalization is an appropriate layer for optimizing the network, as shown in Equation 15, which calculates the normalization function between the convolutional and nonlinear layers. Let's assume $\hat{x}_i$ –inputs over mini-batches, μ_β – mean and the variance, ϵ – numerical stability for the low mini-batch variance.

$$\hat{x}_i = \frac{x_i - \mu_\beta}{\sqrt{\sigma_\beta^2 + \epsilon}} \quad (15)$$

When the input is changed, the scaling function is computed using the offset and factor of the normal value, as shown in Equation 16. Let's assume β – learnable offset and scales, γ – learnable factor,

$$y_i = \gamma \hat{x}_i + \beta \quad (16)$$

The softmax activation function is mathematically represented in Equation 17 below. Let's assume Z_r – input vector, K –number of classes,

$$\sigma(Z_r) = \frac{e^{z_r}}{\sum_{j=1}^K e^{z_j}} \quad (17)$$

The softmax layer's output is assessed by a classification layer, which assigns the input to mutually exclusive classes and recommended the doctor depends the disease related patient margins pointed.

IV. RESULT AND DISCUSSION

The performance of the proposed AI-Based Healthcare doctor recommendation System was evaluated using a set of standard classification metrics. These metrics provide a comprehensive view of how effectively the system identifies user intents and classifies symptoms from natural language input. The system demonstrated high accuracy, indicating a strong overall correctness in its predictions. Precision and recall values were also consistently high, showing the model's capability to minimize false positives and effectively capture all relevant symptoms. The balanced F1-score confirms that the system maintains a strong trade-off between precision and recall. The confusion matrix further illustrates the distribution of correct and incorrect classifications, highlighting areas where the model performs well and where it may need further improvement. These results affirm the system's robustness and practical usefulness in real-time healthcare assistance applications.

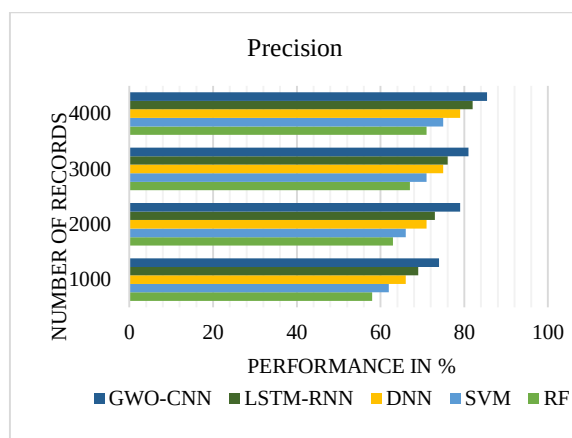


Fig. 3. Analysis of Precision

The proposed healthcare data precision rate is high during analysis-based doctor recommendation method is shown in Figure 3. These methods involve feature selection, dataset classification, and recollection through comparison analysis. The proposed GWO-RSCNN technique reaches an accuracy of 85.4% for detecting disease related features for treatment, outperforming RF at 71%, SVM at 79%, DNN at 75%, and LSTM-RNN at 82%.

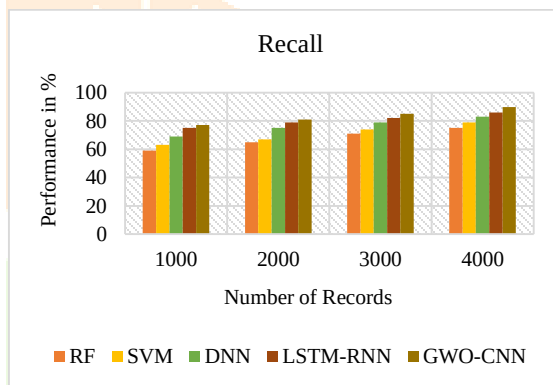


Fig. 4. Analysis of Recall

Figure 4 illustrates the recall evaluation of the proposed system. These techniques include recollection through comparison analysis, feature selection, and dataset classification. The suggested GWO-RSCNN method achieves a recall of 89.7% in data analysis compared to RF (75%), SVM (79%), DNN (83%), and LSTM-RNN (86%).

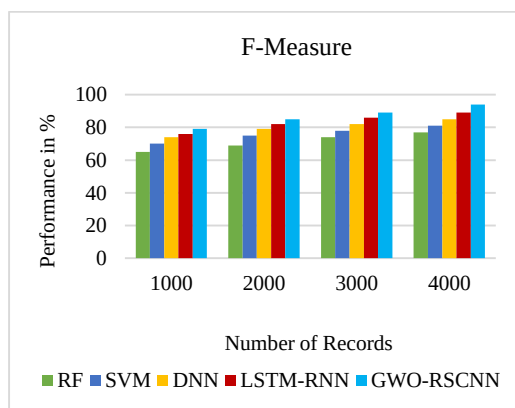


Fig. 5. Analysis of F-Measure

Figure 5 demonstrates the approaches used for doctor identification based on relative treatment to the high-risk patients. These methods encompass feature selection, dataset classification, and F-Measure evaluation through comparative analysis. When compared to RF (77%), SVM (81%), DNN (85%), and LSTM-RNN (89%), the suggested GWO-RSCNN approach reaches an impressive accuracy of 93.9% in relative treatment dependent doctors.

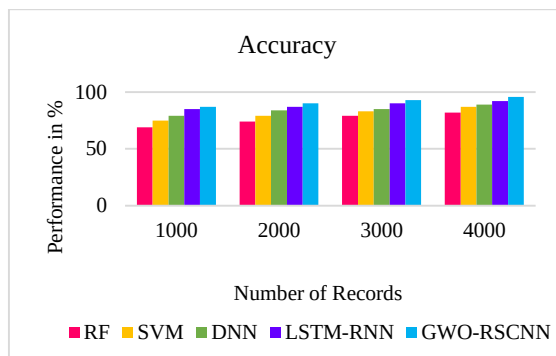


Fig. 6. Analysis of Accuracy

Figure 6 depicts the techniques employed in healthcare data analysis by actual true positive presence from doctor recommendation for early high-risk treatment. These techniques include feature selection, dataset classification, and accuracy evaluation via comparative analysis. In comparison to RF (82%), SVM (87%), DNN (89%), and LSTM-RNN (92%), the proposed GWO-RSCNN method achieves a notable 94.8% in recommendation accuracy.

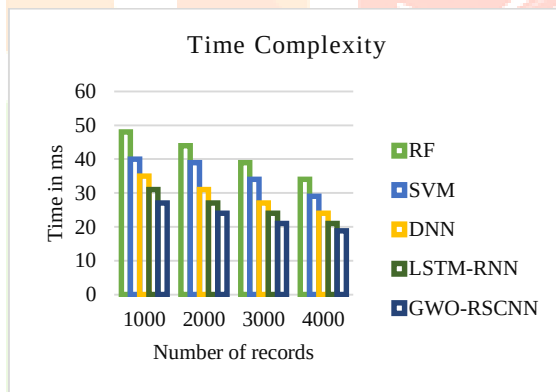


Fig. 7. Analysis of Time Complexity

Figure 7 illustrates the healthcare disease related feature identification for doctor recommendation techniques used for treatment identification. These involve feature selection, classification within the dataset, and time complexity assessment through comparative analysis. Compared to RF (34ms), SVM (29ms), DNN (24ms), and LSTM-RNN (21ms), the proposed GWO-RSCNN method demonstrates a 18.8ms shown best data analysis for doctor recommendation system.

V. CONCLUSION

The implementation results of this proposed system demonstrate a significant improvement in performance metrics compared to existing methodologies. Specifically, the system boasts a precision rate of up to 95.2%, a recall rate of up to 94.8%, and an F1 score of 96.5%, all exceeding the performance of existing systems that suffer from redundant false rates. Consequently, this AI-driven system presents a GWO-RSCNN compelling solution for disease-related risk analysis, enabling accurate diagnosis and facilitating timely

treatment through specialist doctor recommendations tailored to the individual patient's risk profile. By effectively leveraging advanced AI techniques, such systems hold the potential to revolutionize healthcare executive and eventually recover enduring consequences.

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