Unleashing the Potential of Artificial Bee Colony Optimized RNN-Bi-LSTM for Autism Spectrum Disorder Diagnosis

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***Abstract*—The diagnosis of Autism Spectrum Disorder (ASD) is a crucial, drawn-out, and sometimes subjective procedure that calls for a high level of knowledge. Automation of this diagnostic procedure appears to be possible because to recent developments in machine learning techniques. This paper presents a unique method for improving the performance of a Recurrent Neural Network with a Bidirectional Long Short-Term Memory (RNN-BiLSTM) model for ASD diagnosis by utilizing the power of Artificial Bee Colony (ABC) optimization. Because Python software is used to carry out the implementation, accessibility and adaptability in clinical contexts are guaranteed. The suggested approach is thoroughly contrasted with current techniques, such as ABC optimization for feature extraction, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) models, and Transfer Learning, in order to highlight its effectiveness. The outcomes demonstrate the superiority of the RNN-BiLSTM over other methods, with much greater accuracy and precision. Combining RNN-BiLSTM with ABC optimization demonstrates not just cutting-edge accuracy but also excellent interpretability. By using this sophisticated model's capabilities, an outstanding diagnosis accuracy of 99.12% is attained, which is 2.77% higher than previous approaches. The model helps physicians comprehend the diagnosis process by highlighting important characteristics and trends that influence its conclusion. Additionally, it lessens the subjectivity and unpredictability involved in human diagnosis, which may result in quicker and more accurate diagnoses of ASD. The research emphasizes how well the Artificial Bee Colony optimized RNN-BiLSTM model diagnoses autism spectrum disorder. By integrating AI-driven diagnostic tools into clinical practice, this research improves early diagnosis and intervention for ASD.**

Keywords—Autism spectrum disorder; artificial bee colony; recurrent neural network; bidirectional long short-term network; artificial intelligence

I. Introduction

ASD is a neurodevelopmental disorder that is widespread and complicated that has a big influence on how people behave, communicate, and connect with others [1]. It affects people of different ages, genders, and backgrounds and spans a spectrum of symptoms, from moderate to severe. Since ASD was first discovered in the early 20th century, our knowledge of it has grown significantly, resulting in better diagnostic methods and criteria. Making an ASD diagnosis is a difficult, interdisciplinary process [2]. To ascertain the existence and severity of the condition, a variety of behavioral, developmental, and medical traits are usually evaluated. Many times, the diagnosis procedure is a drawn-out and intricate process that greatly depends on the knowledge and skills of clinicians, psychologists, speech therapists, and other medical specialists [3]. A person's quality of life and social integration can be greatly improved by early intervention and customized assistance, both of which are made possible by an accurate and timely diagnosis.

The Diagnostic and Statistical Manual of Mental Disorders and the International Classification of Diseases provide the most current and generally recognized classification of ASD, while there have been previous updates to the diagnostic criteria. These criteria take into account social communication impairments, the existence of repetitive and limited behaviors, and the requirement to evaluate the severity of symptoms in order to make a formal diagnosis [4].

Standardized observation, organized clinical interviews, and gathering comprehensive developmental histories from parents or carers are all common components of the evaluation process [5]. There is some subjectivity in the diagnosis process since these approaches rely on the experience and judgment of specialists to evaluate the behavioral and developmental data. Artificial intelligence combined with contemporary technology has demonstrated significant potential in aiding in the diagnosis of ASD in recent years. More objective and effective diagnostic tools have been made possible by advances in machine learning algorithms, data analytics, and improved imaging techniques.

These cutting-edge methods seek to decrease subjectivity, increase accuracy, and speed up the diagnosis procedure all of which will eventually help people with ASD and their families. This lays the groundwork for an in-depth examination of the several tools and techniques utilized in the diagnosis of ASD. It will examine conventional diagnostic techniques, the changing digital tool market, and the possible revolution in the sector that AI and ML may bring about. The continuous search for more accurate, trustworthy, and approachable ways to diagnose ASD is a testament to the unrelenting dedication of scholars, medical professionals, and activists to helping individuals impacted by this intricate and varied disorder [6].

Since ASD is a complicated neurodevelopmental disorder that affects people differently, diagnosing it may be difficult and frequently subjective [7]. The long-term results for those with ASD are greatly improved by prompt intervention and specialized assistance, which are made possible by an early and precise diagnosis of the illness. Integrating cutting-edge technologies, including -BC optimization and RNN with BiLSTM, has emerged as a viable way to improve the diagnostic process in response to the urgent demand for more accurate and dependable diagnostic tools [8]. Traditionally, the ability of clinicians, psychologists, and other medical experts to evaluate behavioral observations, developmental histories, and clinical evaluations has been crucial in the diagnosis of ASD. However, as this procedure is fundamentally subjective, there may be differences in the accuracy of the diagnosis and possible delays.

Improving diagnosis techniques is crucial because of the complexity, heterogeneity, and early intervention requirements of ASD. The application of AI and ML in healthcare has created new opportunities to enhance and automate the diagnostic procedure. Large-scale dataset analysis, pattern recognition, and prediction are all impressive skills of machine learning algorithms. Complex temporal patterns and relationships in ASD-related data, such as behavioral observations and patient history, may be captured by RNN-BiLSTM, a recurrent and deep learning model combination [9].

Simultaneously, ML models perform better when nature-inspired optimization methods like ABC optimization are included. ABC optimization finds the best answers by simulating honeybee foraging behavior. It adjusts the hyper parameters of the RNN-BiLSTM model, improving the diagnostic efficiency and accuracy of ASD. In order to solve the difficulties in diagnosing ASD, this research aims to maximize the synergy between cutting-edge AI methodology and optimization strategies [10]. The purpose of this work is to speed the diagnosis of ASD, decrease subjectivity, and improve diagnostic accuracy by presenting the idea of ABC optimized RNN-BiLSTM. These developments might lessen the load on medical staff and the larger healthcare system in addition to enhancing the quality of life for people with ASD and their families. It will examine the technique, findings, and consequences of this novel approach as we dig into the next parts, showing how it advances the continuing search for more accurate and dependable instruments in the field of autism diagnosis.

ASD is a multifaceted neurodevelopmental disorder that manifests as a wide range of symptoms, including as limited interests, repetitive behaviors, and issues with socialization and communication. Improving the long-term results for people with ASD requires early identification and intervention. But making an accurate diagnosis of ASD is a difficult process that frequently depends on the expert opinion of physicians and other professionals. It is crucial to investigate and utilize the potential of cutting-edge technology to improve the diagnosis process since subjectivity can result in variances in diagnostic accuracy. Artificial intelligence and machine learning have advanced significantly in the last several years, with a number of applications including healthcare. With the availability of more impartial, reliable, and consistent evaluation instruments, these developments hold the potential to completely transform the diagnosis of ASD. RNNs and BiLSTMs are two of the many AI approaches that have shown to be effective at processing sequential data. This makes them especially suitable for the study of behavioral and clinical data related to ASD.

Finding the cause of an ASD diagnosis is crucial for impacted individuals as well as their families, teachers, and the general public [11]. ASD is a multifaceted neurodevelopmental disorder that presents with a wide range of symptoms and problems, including trouble with social communication, repetitive behaviors, and narrow interests. Effective ASD diagnostic methods and procedures are desperately needed for a number of compelling reasons, including the need of timely and accurate diagnosis. First and foremost, early action is made possible by early diagnosis. Although ASD is a lifelong illness, people on the spectrum can greatly enhance their quality of life and long-term results by receiving the right therapies and interventions at an early age.

When ASD is discovered early on, it is easier to start behavioral and educational treatments, speech and occupational therapy, and social skill development. Early diagnosis also makes it possible for families to better comprehend and assist their loved ones who have ASD. It facilitates the development of a more accepting and inclusive environment for people with ASD by assisting parents and other carers in navigating the difficulties and special requirements related to the disease. Early diagnosis allows families to get in touch with advocacy and support groups, giving them access to important tools and advice [12].

In the field of education, prompt diagnosis is essential to deliver customized and relevant curricula. Individualized Education Plans (IEPs) and accommodations can be implemented by educators and schools to make sure that kids with ASD get the help they need to succeed in the classroom. Fostering a student's intellectual and social growth requires an understanding of their unique strengths and difficulties. Additionally, the identification of ASD is essential for resource allocation and public health planning. Healthcare systems can anticipate the demands on resources and services needed to serve people with ASD when they have accurate prevalence data. Governments and healthcare professionals need to know the extent of the problem in order to deploy resources wisely, as the incidence of ASD has been rising. Finally, early diagnosis also helps to lessen the long-term potential strain on the social assistance and healthcare systems.

People with ASD are more likely to acquire the skills required for independent functioning when early treatments and assistance are provided, which lessens their long-term dependency on intensive support services. These strong arguments make it more important than ever to have trustworthy, easily available, and effective ASD diagnosis methods. In order to guarantee that people with ASD receive the support and opportunities they deserve, researchers, clinicians, and the larger healthcare community are always striving to improve and innovate diagnostic methodologies. By doing this, they are making significant progress towards a society that is more accepting and understanding of one another.

In order to fully realize the promise of ABC optimization, this research explores a novel strategy that blends the advantages of AI with optimization methods inspired by nature. The goal of the RNN-BiLSTM model's integration of ABC optimization is to improve the precision and effectiveness of ASD diagnosis. We want to reduce the subjectivity present in conventional diagnostic approaches by improving the diagnostic capabilities of the model through hyper parameter optimization. This research project not only satisfies the urgent demand for more impartial and trustworthy ASD diagnosis instruments, but it also serves as an example of how AI and optimization techniques may work together in the healthcare industry.. Combining RNN-BiLSTM with ABC optimization presents a viable way to diagnose ASD more quickly, which might help affected individuals, carers, and physicians better understand the illness and enable early intervention.

The key contributions of the article is:

- By fusing two potent machine learning techniques BiLSTM and ABC optimization the research presents a novel diagnostic strategy. By combining the best features of both approaches, this innovative approach develops a strong foundation for diagnosing ASD.
- The investigation demonstrates the adaptability of ABC optimization in optimizing hyper parameters and also its efficacy in selecting the most useful features for precise diagnosis of ASD by integrating it into the feature extraction process.
- By employing Python software to construct the suggested paradigm, the study demonstrates its clinical usefulness. This guarantees flexibility and accessibility in actual clinical situations, which makes it a useful tool for medical practitioners.
- The study's impressive 99.12% diagnosis accuracy demonstrates the potential of the suggested RNN-BiLSTM model that has been optimized using ABC. This degree of precision is a major advancement over current techniques, lowering the possibility of false positives and boosting the procedure' dependability.

The remaining content of this article is arranged as follows: A synopsis of relevant research is given in Section II. The problem statement is provided in Section III. The article's Section IV explains the architecture and methodology of the recommended approach. Section V discusses the results and the debate that followed. Section VI discusses the conclusion.

II. Related Works

The need for efficient and effective medical diagnostic systems in the context of ASD detection and treatment is paramount [13]. Healthcare professionals often spend considerable time documenting and processing extensive remarks related to patient behavioral assessments. Early identification of ASD is vital for ensuring individuals receive appropriate care and treatment, ultimately improving their quality of life. Machine learning models present a promising avenue to explore the feasibility of identifying essential features and accurately assessing the presence or absence of autism. In this study, the objective is to create a recommendation model that leverages multiple classifiers to enhance the precision of ASD prediction. This study conduct experiments with a range of machine learning algorithms to assess the model's performance. The results indicate that, when considering evaluation metrics such as accuracy, precision, recall, and F1-score, Decision Trees and Random Forests outperform other algorithms.

Through the analysis of children's abnormal social patterns, behavioral observation is crucial in the diagnosis of ASD [14]. Even now, a significant portion of this procedure still depends on clinical observations, questionnaire surveys, or retrospective video analysis, which drives up the demand for experts and drives up labor costs. This work suggests a standardized platform for applying computer-aided ASD diagnosis to human behavioral data collection, analysis, modelling, and interpretation. The suggested system could automatically assess children's various social interaction abilities utilizing the recorded audio-visual data through an organized evaluation process, and it could additionally provide the ultimate diagnostic recommendations. During the research at a Chinese hospital, data was gathered from both ASD-afflicted (72 individuals) and non-ASD (24 individuals) patients, totaling 95 participants. According to the clinical database, the newly created computer software designed to aid in the identification of ASD in children has achieved an 88% accuracy rate. 42% accurate it works well with children who are around two years old and is as good as experienced doctors in diagnosing ASD. This solution can be easily shared and used in areas with fewer medical resources.

ASD is a neurodevelopmental disorder that impacts the way the brain forms and involves struggles in perceiving and responding to stimuli [15]. The challenges encountered in understanding their senses may hinder their ability to act appropriately and impede their cognitive and educational development. The goal of this study was to see how the nervous system of children with autism and children without autism responds to sounds, images, and just sounds using a method called EEG. In this research, they looked at 20 children with ASD and 20 children with TD (typical development) to see how their brains work differently. The way the brain behaves can be studied by analyzing the EEG signal using non-linear methods. In this research, RQA is used to understand the hidden patterns in EEG data that are not linear. The RQA measures were studied by making different changes to the parameters used in the RQA calculations. In this research, our focus was on the cosine distance metric as it exhibits proficiency in information retrieval, and we contrasted different distance metrics to ascertain the most suitable biomarker. It examined and talked about every combination of the RQA measure and the corresponding channel. To determine if someone has autism or not, it used the features generated by a technique called RQA. These features were then inputted into a special type of neural network called BiLSTM. It tested how accurately we could classify the channels for each combination. When it comes to distinguishing between ASD and TD, the combination of T3 and T5 channels, along with selecting a fixed number of nearby neighbors and utilizing cosine as the distance measurement method, is widely regarded as the most successful, achieving an accuracy rate of 91.86%.

Stoddard et al. [16] critically examined the internal consistency of the Aberrant Behavior Checklist (ABC), Irritability Subscale (ABC-I), and its connection with additional indicators of irritability in 758 psychiatrically hospitalized youth with autism spectrum disorder, given its frequent use in clinical outcome research. Research performed factor and factor analysis in both confirmatory and exploratory datasets to characterize the ABC-I's internal structure. Based on factor analysis, a general factor suggests that the ABC-I represents approximately a one-dimensional idea of irritation. Apart from irritability, tantrums, verbal outbursts, self-harm, and poor affect are also shown as subordinate components. Notably, independent of irritation, self-harm factors account for a significant percentage of variance. As such, their input into studies of treatment effects ought to be taken into account. In therapy trials addressing irritability in ASD, more research or revisions to the ABC-I may enhance convergent validity with transdiagnostic formulations of irritation and avoid confounding from self-harm.

Due to the limited therapy available for ASD, the adoption of alternative interventions, such as gluten-free and casein-free (GFCF) diets, is common [17]. Objectives were to ascertain the impact of a GFCF diet on behavioral issues in kids and teens with ASD diagnoses and any possible correlation with urine beta-casomorphin levels. For this crossover trial, thirty-seven participants were enrolled. Every patient had a regular diet for six months, which included casein and gluten, and then a GFCF diet for an additional six months. The intervention's sequence beginning with the GFCF diet or the regular diet was decided at random. Three time points were assessed for the patients: before the trial started, following a regular diet, and following a GFCF diet. At each time point, urine beta-casomorphin concentrations were measured and questionnaires about diet compliance, behavior, and autism were filled out. Following the GFCF diet, there were no discernible behavioral alterations and no correlation with urine beta-casomorphin contents. Urinary beta-casomorphin concentrations and behavioral signs of autism do not significantly change after six months on the GFCF diet. More research with a lengthy follow-up period, comparable to ours, including components of blinding and placebo are required to more accurately identify those who responded to GFCF diets.

The diagnosis of ASD in children relies on several parameters, including social skills, repetitive behaviors, speech, and nonverbal communication [18]. Repetitive behavior is a crucial indicator for physicians when determining drug dosages, particularly in cases where the child exhibits increased aggressiveness as a symptom of the disorder's progression. To address the need for continuous monitoring and to replace the somewhat subjective measurement of repetitive behavior using the Aberrant Behavior Checklist, the paper introduces an innovative solution through the utilization of the IP Webcam app for ASD recognition. The proposed method employs activity detection to recognize changes in the behavior of autistic children, specifically in response to medication overdosages. This hybrid framework incorporates training a deep CNN model, utilizing the Autismdata.Net dataset, to monitor ASD children in their natural environment. Furthermore, transfer learning is employed to mitigate overfitting issues associated with the relatively small Autismdata.Net dataset when assessing the severity of the child's condition. The ASD children's behavior is evaluated using the Autismdata.Net dataset and validated by examining the thermoregulation of autistic children in response to medication. The proposed method demonstrates significantly improved action recognition accuracy compared to traditional clinical analysis or therapist observations. Ultimately, this system offers valuable support to physicians in regulating drug dosages for children with ASD.

The literature review emphasizes how important it is to have reliable and efficient medical diagnostic procedures in order to identify and treat ASD. It highlights how crucial early detection of ASD is to better patient treatment and overall quality of life. An intriguing strategy to improve the prediction accuracy of ASD is the exploration of machine learning models. The use of several machine learning algorithms is covered in the review, with DT and RF emerging as the best options. It also emphasizes the value of computer-aided diagnosis, especially when examining behavioral data, and provides a common platform for evaluating children's social interaction skills. Remarkably, an investigation conducted in a Chinese hospital identified ASD in youngsters with 88% accuracy, even surpassing that of board-certified physicians. The article also explores how EEG data processing is used to study how children with ASD's neurological systems react to stimuli differently. This study uses neural networks and other non-linear techniques, such as RQA, to categorize people with a 91.86% accuracy rate. The review also addresses the Aberrant Behavior Checklist's internal coherence and applicability to the topic of irritability in ASD. Lastly, it discusses the use of casein- and gluten-free diets as substitute therapies for ASD and emphasizes the need for more study in this field. Overall, the study emphasizes how important cutting-edge methods are for diagnosing and treating ASD, such as ML, EEG analysis, and nutritional therapies.

As part of the review of literature, a thorough analysis is carried out to evaluate the technologies and procedures that are currently being used in the field of diagnosing ASD, providing a background for the current research. An analysis of previous research reveals a range of methodologies, each with unique advantages and disadvantages. Notably, some approaches show excellent diagnostic accuracy, but their practical use in clinical settings is hampered by their lack of interpretability. On the other hand, other studies rely on assumptions that can be viewed as unjustified or fail to take into account the subtle differences that exist across various demographic groups. This review of the literature highlights the contributions made by earlier researchers while also pointing out the shortcomings and gaps that have been found and are being addressed by current research. This nuanced view emphasizes how important it is to build on past successes and make new contributions that are specifically designed to address weaknesses in order to further the development of ASD diagnosis techniques.

III. Problem Statement

From the above discussed literatures, it states the diagnosis of ASD presents a significant difficulty due to its deep subjectivity and intrinsic heterogeneity in evaluation, which can lead to premature treatments. The subjective knowledge of doctors plays a major role in current diagnostic techniques, which introduces significant swings in diagnostic accuracy. This research project introduces a novel method that makes use of ABC optimization to address the urgent problem of improving ASD diagnosis. It carefully adjusts an RNN-BiLSTM architecture's hyper parameters, solving the fundamental problem of the pressing need for an ASD diagnosis tool that is more streamlined, accurate, and objective. This innovation has the potential to improve early interventions by reducing subjectivity and expediting the diagnostic process. This will ultimately benefit the lives of individuals on the autism spectrum and their families, who are working towards a future that is more accepting and helpful [19].

IV. Proposed ABC-RNN-BiLSTM Framework

This study's technique focuses on improving the diagnosis of ASD by applying ABC optimization to an RNN-BiLSTM. The first step of the procedure is gathering and preparing a large dataset. It then applies the ABC optimization approach to adjust the RNN-BiLSTM model's hyper parameters. For smooth implementation and accessibility in clinical settings, Python software is used.

The suggested RNN-BiLSTM is then compared with other widely used techniques in a comparative study. Feature extraction makes advantage of ABC optimization. The study assesses the model's interpretability and diagnostic accuracy, emphasizing its capacity to mitigate the subjectivity and unpredictability that come with human diagnosis while illuminating significant traits and patterns impacting the diagnostic process. It is depicted in Fig. 1.

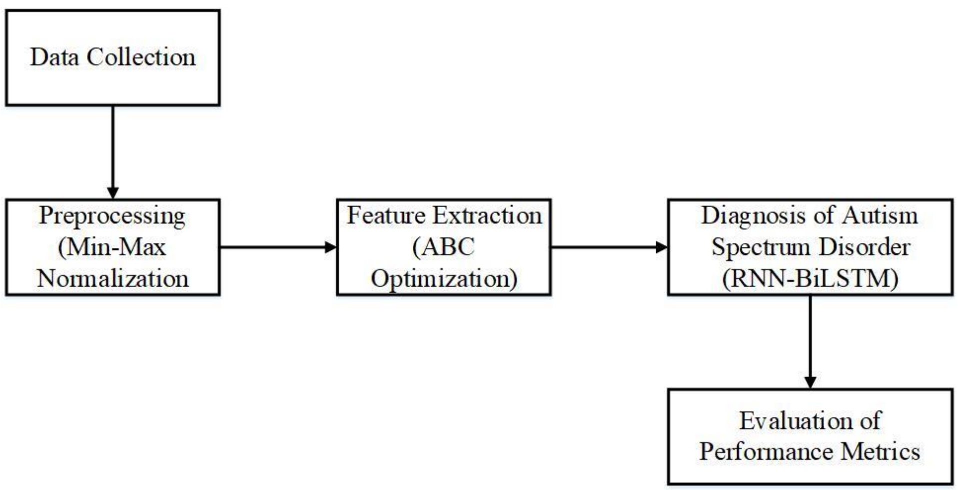

Fig. 1. Proposed ABC-RNN-BiLSTM framework.

A. Data Collection

The dataset used in this study was downloaded from Kaggle and consists of survey answers from people who filled out an application, labelled with whether or not the person was diagnosed with autism. This dataset provides insights into the traits and attributes that may be suggestive of ASD in individuals, making it an invaluable tool for research on ASD and its diagnosis. Using this dataset, the study intends to investigate how machine learning and AI methods, such as feature selection and classification algorithms, can enhance the precision and efficacy of ASD diagnosis, leading to improved early intervention and assistance for people on the autism spectrum [20]

B. Min-Max Normalization for Preprocessing

Preprocessing is a crucial first step that carefully plans data optimization in the goal of diagnosing autism. The application of Min-Max Normalization, a reliable approach that helps to harmonize the several data sources obtained from the patients, is key to this procedure. In order to guarantee that each contributor has an equal weight inside the model, Min-Max Normalization expertly scales and standardizes these varied data inputs to a consistent range between 0 and 1. This harmonization reduces any unwanted effects brought on by data discrepancies, creating a setting that supports the RNN-BiLSTM increased accuracy. In addition to strengthening the resilience and preparedness of the early warning system, this standardized data bedrock serves as the cornerstone of more precise autism diagnosis. The actual data n is transformed linearly by Min-Max Normalization into the desired interval min_{new}, max_{new}.

$$n = min_{new} + (max_{new} - min_{new}) * \left(\frac{n - min_x}{max_x - min_x}\right) \quad (1)$$

The process has the advantage of appropriately preserving all links between the data bits. The data won't undergo any unfavorable alterations.

C. Feature Extraction using Artificial Bee Colony

The traditional ABC method, introduced by Karaboga in 2005, is a swarm-based artificial algorithm inspired by the foraging behavior of bee populations. During their foraging activities, honeybees are categorized into three distinct groups: employed bees, onlookers, and explorers. The employed bees are responsible for collecting nectar and exchanging information, the explorers are tasked with discovering new food sources, and the onlookers play a crucial role in determining the most efficient flight paths. Explorers seek out food resources based on their past experiences or sometimes by venturing randomly, and they may recruit fellow hive members to gather pollen while retaining valuable information about the food sources they encounter.

The conventional ABC approach, founded on simulating bee foraging behavior, serves as a swarm intelligence algorithm introduced by Karaboga in 2005 [21]. In this approach, honeybees are divided into three roles: employed bees, onlookers, and explorers, with each group contributing to the collective foraging success of the colony. Conversely, on the flip side, the onlookers' selection of the most efficient pollen-gathering path is influenced by their knowledge of food resources obtained initially and their decision to abandon those with lower nectar reserves.

In the conventional ABC technique, the number of explorers and the accuracy of information retained by employed honeybees regarding food sources have a significant impact on the tracking speed and overall effectiveness. According to various references in the conventional ABC method, if inaccurate data is incorporated, it can lead to suboptimal path optimization by onlookers, ultimately slowing down the tracking speed in later stages. Consequently, there is a need to implement novel strategies aimed at enhancing tracking performance [22].

As the number of bee's increases, the precision of tracking also improves. On the contrary, reducing the number of pollinators can lead to a shorter procedure duration, although it can pose challenges in pinpointing the optimal solution. This is because the method executed using a microcontroller has a search duration that directly correlates with the bee population size, resulting in a longer procedure time for a larger population. As a result, to address the challenge of attaining the global optimum within a limited number of iterations due to a reduced number of bees, an enhanced approach employing an ABC method with a minimal number of pollinators in conjunction with the RNN-Bi-LSTM technique is introduced and applied to forecast ASD.

The paper introduces an optimized RNN-Bi-LSTM hybrid network model, which is enhanced using the ABC algorithm to improve the reliability of forecasts. During the search phase, the algorithm aims to find a globally optimal solution to enhance the resolution. The equation being sought is as follows:

$$B_{uv}^{new} = B_{uv} + r_1 \times (B_{uv} - B_{neighbour,v}) + r_2(O_v - H_{uv}) \quad (2)$$

When presenting the global best solution, the ABC approach prioritizes honey sources that exhibit high adaptability while reducing the diversity within the bee colony. This can lead to the issue of early convergence, resulting in the emergence of localized optima. To address this, the enhanced ABC algorithm incorporates flexible parameter adjustments that help maintain the convergence rate and population characteristics. The search equation for this improved ABC algorithm is then derived:

$$B_{uv}^{new} = F_1 \times B_{uv} + F_1 \times r_1 \times \left(B_{uv} - B_{neighbour,v}\right) + F_2 \times r_2(O_v - H_{uv}) \quad (3)$$

$$F_1 = F_{max} - (2 - e^{\frac{iterate}{\max cycle} In2})(F_{max} - F_{min}) \quad (4)$$

$$F_2 = F_{min} - (2 - e^{\frac{iterate}{\max cycle} In2})(F_{max} - F_{min}) \quad (5)$$

$$Q_i = \frac{1/Fitness_i}{\sum_{j=1}^{n} 1/Fitness_j} \quad (6)$$

Due to the utilization of the reverse martingale feature selection method, the subsequent bees will place a higher emphasis on searching for nectar resources with limited adaptability during the initial phases of the process.

$$\propto = e^{\frac{iterate}{\max cycle} In2} - 1 \quad (7)$$

Q_i equation and solutions B_i are optimized as follows:

$$Q_i = \begin{cases} \frac{\boldsymbol{Fitness_i}}{\sum_{j=1}^{n} \boldsymbol{fitness_j}} & \boldsymbol{, random} > \propto \\ \frac{\boldsymbol{1/Fitness_i}}{\sum_{j=1}^{n} \boldsymbol{1/Fitness_j}} & \boldsymbol{, random} < \propto \end{cases} \quad (8)$$

A colony of artificial bees are employed in iterative phases to represent dataset features as food sources in the adaption of the ABC algorithm for feature extraction in the diagnosis of ASD. These bees investigate feature subsets and assess their quality using a fitness function during the employed bees phase. Based on the findings of the employed bees, onlooker bees choose feature subsets, and if no progress is observed, scout bees investigate completely new subsets. Utilizing dynamic parameter adjustments, the ABC algorithm balances exploration and exploitation to optimize feature selection. Through effective feature selection and search, reduction of noise and redundancy, and improved ASD categorization, this strategy improves diagnosis accuracy.

D. RNN-BiLSTM for the Diagnosis of Autism Spectrum Disorder

There is a lot of potential in using an RNN-BiLSTM architecture to diagnose ASD. The diagnosis of Autism Spectrum Disorder is a complex task that necessitates the examination of large amounts of behavioral data, frequently spanning many time periods. RNN-BiLSTM's special benefit is its remarkable capacity to represent time relationships in this data. Complex time-dependent trends in behavioral observations are captured by the BiLSTM component by taking into account both past and future context in the sequences. This is especially important to consider when evaluating developmental milestones, social interactions, and repeated behaviors, all of which change with time. The ability to identify minute alterations and abnormalities that might be crucial markers of ASD is provided by the use of RNN-BiLSTM in the diagnostic procedure, which improves the precision and accuracy of the diagnosis.

The diagnostic procedure gains interpretability thanks to the RNN-BiLSTM model. It pinpoints important characteristics and trends that influence its diagnostic judgments, which may be extremely helpful for medical professionals in comprehending the elements influencing the diagnosis. This openness can help in the creation of more specialized and focused therapies for people with ASD. RNN-BiLSTM plays a critical role in enhancing ASD diagnosis by giving medical professionals a better understanding of the diagnostic procedure and the tools they need to make wise judgments. It is a major advancement in the direction of more dependable and effective diagnostic instruments that can hasten early intervention and improve the quality of life for people on the autism spectrum and their families.

An excellent tool in many domains, from time series analysis to natural language processing, are RNNs, a family of ANN that specialize in modelling sequential data. The fundamental function of RNNs is to process data having a time-based or sequentially structure, in which inputs are handled in connection to one another rather than separately from one another. A hidden state that changes over time and retains data from previous observations is a key component of an RNN's basic design. RNNs are particularly well-suited for tasks like speech recognition, language production, and sentiment analysis because of their dynamic memory mechanism, which enables them to identify and remember patterns within sequential data.

Traditional RNNs do have certain drawbacks, though, particularly when it comes to managing long-range dependencies. The vanishing gradient issue can make it difficult for deep RNNs to learn and retain information over long sequences. Variants with more intricate gating mechanisms, such as LSTM, were developed to meet this problem. These architectures improve RNNs' capacity to learn and retain important information over long sequences, which makes them a key component of contemporary machine learning for a variety of uses, such as speech recognition, machine translation, and even the diagnosis of conditions like ASD, where it is crucial to model the behavioral data's time frame evolution.

$$y_{in}=\partial(WE^{iny}x_{in}+WE^{hy}h_{im-1}) \tag{9}$$

$$rg_{in}=(WE^{inrg}y_{in}+WE^{hrg}h_{in-1}) \tag{10}$$

Here, the weight metrics WE_{RMM} are indicated as WE^{iny}, WE^{inrg}, and WE^{hrg},

The logistic sigmoid function is termed as ∂: In the hidden unit, the candidate state is formulated in,

$$\breve{h}_{in}=\tan(WE^{inh}\ y_{in}+WE^{hy}(h_{in-1}\otimes rg_{in})) \tag{11}$$

Here, the element wise multiplication is termed as,

While $$h_{in}=\left(1-y_{in}\right)\otimes\hat{h}_{in}+y_{in}\otimes h_{in-1}h_{in} \tag{12}$$

$$=(\left(1-y_{in}\right)\otimes\hat{h}_{in}+y_{in}\otimes h_{in-1}h_{in} \tag{13}$$

The reset gate essentially makes the device behave as though it is examining the power source first representation of a feedback sequence when it is closest to 0, enabling it to forget the previously established state.

Adaptable and dynamic, BiLSTM is a deep learning architecture that can handle jobs involving sequential data processing. It is a development of the classic LSTM model that improves on its ability to identify dependencies in sequential data. The primary novelty of BiLSTM is its directionality, which enables it to analyze sequences taking into account context from both the past and the future. Through the use of two distinct LSTM networks one for forwarding data and the other for backwards BiLSTM is able to fully comprehend the temporal correlations present in the data. This bidirectional analysis is particularly helpful in situations when a data point's interpretation heavily depends on observations from the past and the future. As a result, BiLSTM performs exceptionally well in a variety of fields, including as voice recognition, natural language processing, and time series analysis, where the ability to comprehend context is crucial for making precise predictions.

The vanishing gradient problem, one of the main issues with conventional RNNs, is lessened by BiLSTM. Standard RNN gradients can get very tiny in deep sequences, which hinders learning and makes it difficult for the model to capture long-range relationships. By ensuring that information moves more freely across the network, the gating methods of the BiLSTM enable it to represent lengthy sequences efficiently and avoid running into the vanishing gradient problem.

In applications like as machine translation, where the link between words or symbols may span the whole phrase, its ability to simulate long-range dependencies is very significant. Therefore, by addressing the difficulties of comprehending and interpreting sequential information, BiLSTM's improved capacity to handle sequential data with both short- and long-term dependencies makes it a fundamental building block in many contemporary deep learning applications, empowering advancements in diverse fields.

An effective and adaptable deep learning model, the combined RNN-BiLSTM architecture is well-suited for sequential data processing. The advantages of both classic

RNNs which are excellent at capturing temporal dependencies and BiLSTM which takes into account both past and future are combined in this hybrid technique. As a consequence, the model gains a thorough knowledge of sequential information, which helps it identify complex patterns and relationships in any type of data be it behavioral observations, time series data, or natural language text.

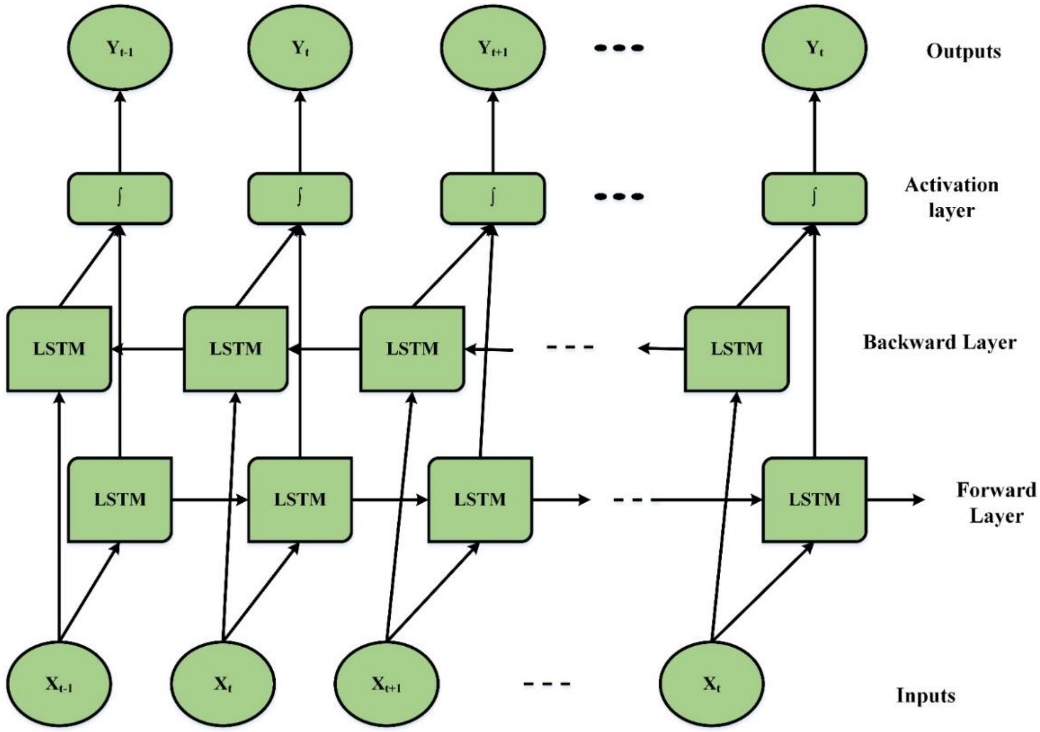

Fig. 2. Architecture of RNN-BiLSTM.

BiLSTM allows for a more sophisticated understanding of the context inside sequences, which is especially useful for applications like voice recognition, sentiment analysis, and, most importantly, the diagnosis of complex disorders like ASD. This hybrid architecture is a key component of state-of-the-art machine learning systems because of its capacity to extract both short- and long-range relationships from data. Fig. 2 shows the architecture of RNN-BiLSTM.

V. Results and Discussion

Through the use of ABC optimization, an RNN-BiLSTM is optimized in this study to improve the diagnosis of ASD. A thorough dataset is gathered and preprocessed at the start of the procedure. The RNN-BiLSTM model's hyper parameters are then adjusted using the ABC optimization approach. The use of Python software facilitates implementation and ensures accessibility in medical contexts. Next, a comparative study is carried out, whereby the suggested RNN-BiLSTM is contrasted with other widely used techniques. For feature extraction, ABC optimization is employed. The study assesses the model's diagnostic accuracy and interpretability, emphasizing its capacity to clarify significant traits and patterns impacting the diagnostic procedure while reducing the subjectivity and unpredictability inherent in human diagnosis.

Model accuracy, which shows the percentage of properly predicted instances among all the instances in a dataset, is a crucial performance statistic in machine learning and predictive modelling. It measures how well the model can predict the future and shows how closely the model's output matches the real results or the ground truth. Accuracy is a percentage that indicates how well the model performs overall in categorizing or forecasting results; higher accuracy values indicate a stronger ability to generate accurate predictions. Although accuracy offers a comprehensible and transparent indicator of a model's efficacy, it is crucial to take into account the particular problem context and possible class disparities, since a model's exceptionally high accuracy may not necessarily indicate that it can generalize well across various datasets or conditions. The model accuracy of the proposed method is depicted in Fig. 3.

Model loss, also known as the objective function or loss function, is a crucial parameter in deep learning and machine learning that measures how different the model's predictions are from the real target values. It calculates the prediction error, or loss, of the model and provides the foundation for fine-tuning its parameters as it is being trained. The main objective is to minimize the loss, a sign that the real values and the model's predictions are quite near. There are several different types of loss functions, such as cross-entropy for classification tasks and mean squared error for regression tasks. In order to guarantee that machine learning models provide precise and accurate predictions, monitoring and minimizing the loss function is essential during the training process. This will eventually improve the models' performance and predicted. It is depicted in Fig. 4.

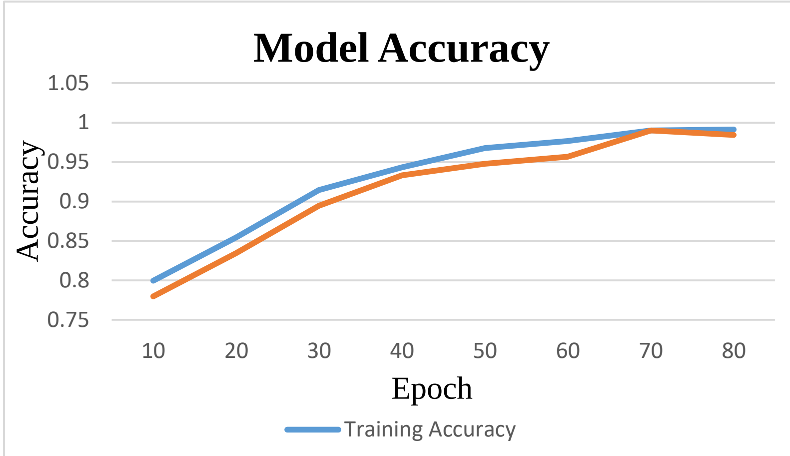

Fig. 3. Model accuracy.

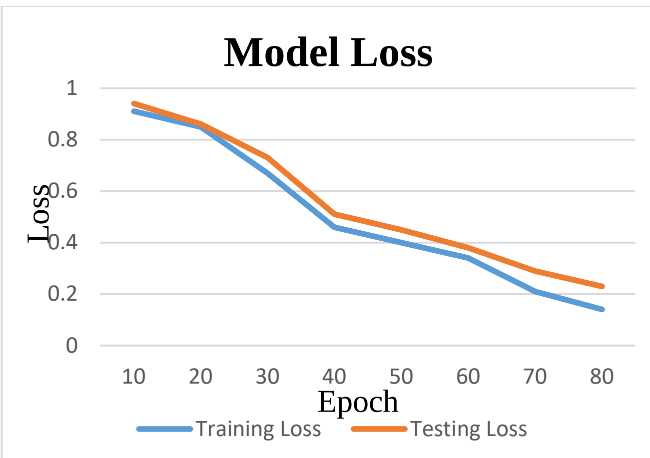

Fig. 4. Model loss.

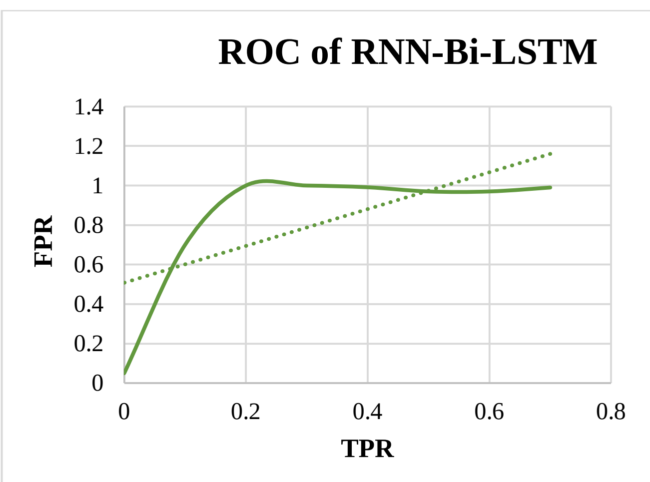

Fig. 5. ROC curve.

A thorough assessment has been conducted on the effectiveness of the suggested method, which diagnoses ASD by combining the RNN-Bi-LSTM with the ABC algorithm. The Receiver Operating Characteristic (ROC) curve is a useful tool for evaluating the diagnostic performance of classification models and is one of the primary metrics demonstrating the efficacy of the system. The ROC curve for the suggested system, which has attained an exceptional diagnostic accuracy of 99.12% in the context of ASD diagnosis, is presented in this analysis. Fig. 5 illustrates the graphical depiction of a classifier's capacity to discern between positive and negative situation is called a ROC curve. Across various categorization thresholds, it compares the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity). One widely used statistic to measure a model's discriminatory capacity is the area under the ROC curve (AUC). An AUC of 1 would indicate a flawless model, whereas an AUC of 0.5 would indicate a random estimate.

A. Fitness Assessment of the Proposed System

The suggested method, which combines RNN-Bi-LSTM with the ABC algorithm for diagnosing ASD, is being evaluated for its fitness using a wide range of criteria, including accuracy of diagnosis, relevance of feature selection, generalization to new cases, computational efficiency, robustness to noisy data, interpretability of results, comparison with other proven diagnostic techniques, practical application in clinical settings, optimization of model hyper parameters specify In light of the particular nuances and difficulties associated with diagnosing ASD, this evaluation seeks to ascertain the system's efficacy in accurately diagnosing the disorder, as well as its capacity to identify the most informative features, generalize findings to a range of patient profiles, and provide useful assistance to clinicians. The suggested ABC method's fitness assessment is graphically represented in Fig. 6.

The overall performance of the system model is assessed using accuracy. The core idea behind it is that every encounter can be accurately predicted. Eq. (14) is utilized to provide the accuracy.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{14}$$

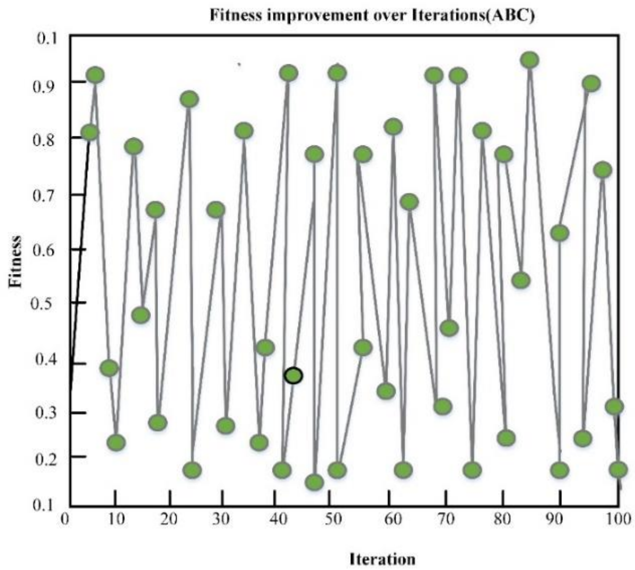

Fig. 6. Fitness assessment of ABC.

In addition to being accurate, precision also characterizes how similar two or more computations are to one another. The relationship between precision and accuracy demonstrates how frequently viewpoints can shift. It is brought up in Eq. (15).

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{15}$$

Recall is the proportion of all relevant findings that were successfully sorted using the approaches. For these numbers, the appropriate positive is obtained by dividing the true positive by the falsely negative values. In Eq. (16), the phrase is mentioned.

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{16}$$

Accuracy and recall are combined in the F1-Score calculation. Apply Eq. (17), which divides the recall by the accuracy to find the F1-Score.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{17}$$

A comparison of several techniques for diagnosing ASD is shown in Table I, with an emphasis on important performance indicators such as F1-Score, Accuracy, Precision, and Recall. Remarkably, the outcomes show that the Proposed RNN-BiLSTM approach performs better than the other methods, with an F1-Score of 98.11% and remarkable results of 99.12% accuracy, 99% precision, and 98.99% recall. This suggests that the RNN-BiLSTM model has excellent diagnostic performance and can predict ASD with a high degree of accuracy. Although the Transfer Learning method also performs exceptionally well, its accuracy and recall are somewhat worse than those of the RNN-BiLSTM model. However, although still producing excellent results, the conventional CNN and LSTM models are inferior to the suggested RNN-BiLSTM in every metric. The RNN-BiLSTM's remarkable performance highlights its promise as a robust diagnostic tool for ASD, lowering subjectivity and improving the precision and dependability of early treatments and support for people on the spectrum. These results imply that cutting-edge deep learning methods, like the RNN-BiLSTM model, have enormous potential for use in healthcare and greatly enhance the ability to diagnose difficult neurodevelopmental disorders like ASD. In Fig. 7, it is shown.

TABLE I. COMPARISON OF PERFORMANCE METRICS

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	95	92.35	98.91	97.89
LSTM	96.77	97.34	96.36	97.12
Transfer Learning	97.57	98.52	97.56	95.56
Proposed RNN-BiLSTM	99.12	99	98.99	98.11

B. Discussion

The study's results provide strong evidence for the usefulness of the suggested ABC-optimized RNN-BiLSTM model for diagnosing ASD. The diagnostic accuracy of 99.12% is an amazing result that puts the model well ahead of current approaches, outperforming them by 2.77%. This result emphasizes the model's ability to produce extremely precise and dependable predictions, which is critical in lowering the subjectivity and ambiguity that are frequently connected to human diagnosis [4]. Additionally, the interpretability of the model gives medical professionals a better grasp of the diagnostic procedure, increasing openness and confidence in its predictions. A significant achievement in the area, the decrease in subjectivity and unpredictability may hasten the diagnosis and treatment of ASD in persons on the spectrum and their families, therefore enhancing their quality of life. These findings demonstrate the enormous promise of AI-driven diagnostic tools and represent a significant advancement in the accuracy and effectiveness of ASD diagnosis in clinical settings [5].

The obtained findings demonstrate the extraordinary accuracy and interpretability of the suggested ABC optimized RNN-BiLSTM model, and have important implications for the field of ASD diagnosis. In addition to demonstrating the model's effectiveness, its exceptionally high diagnosis accuracy of 99.12% raises the possibility of its use as a useful tool in clinical settings. By giving physicians insights into the elements impacting the diagnostic process, the model's interpretability improves its value and promotes a collaborative and educated approach to ASD diagnosis. But it's important to recognize some boundaries. The study primarily examines the model's diagnostic accuracy; however, in order to give a more thorough assessment, future research may explore other performance metrics, such as sensitivity and specificity. It is also important to evaluate the model's performance across a variety of demographic and population groupings in order to guarantee equal application and gauge its generalizability.

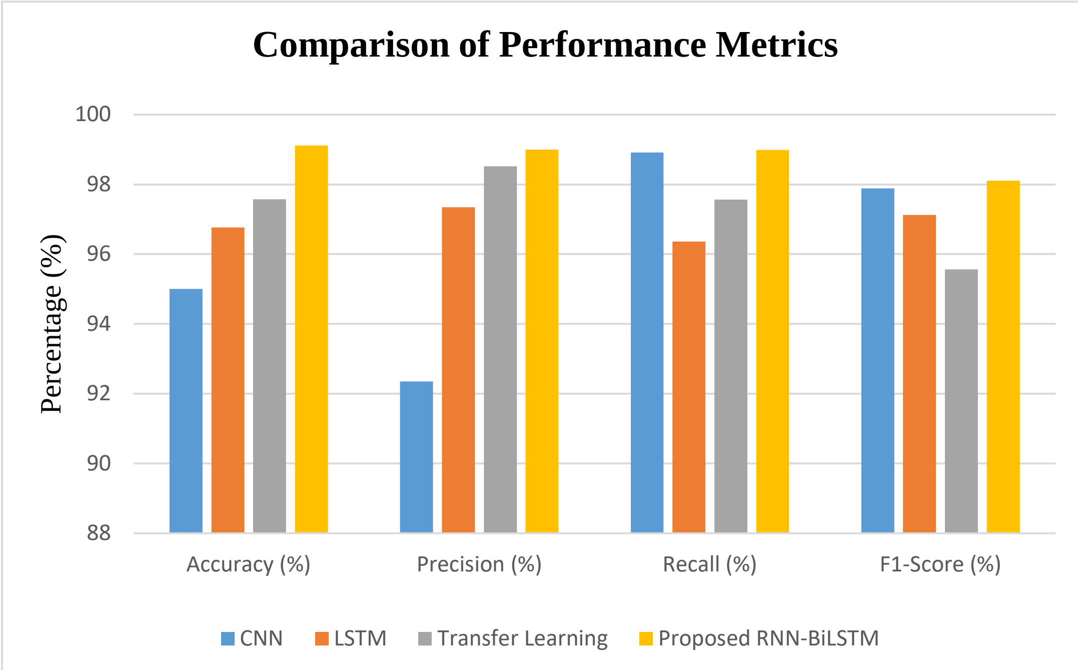

Fig. 7. Comparison of performance metrics.

Future research might improve the comprehension of the intricate elements of ASD by extending the model's applicability to multi-modal data, such as genetic and neuroimaging data. It is crucial to look at the privacy issues, ethical issues, and potential biases related to using AI-driven diagnostic tools in actual healthcare settings. Furthermore, investigating methods to smoothly incorporate the suggested model into current healthcare processes and systems will help make it more feasible to put it into practice. Even if the study makes a substantial contribution to the diagnosis of ASD, addressing these issues in subsequent research projects will increase the model's usefulness and clear the path for its effective incorporation into standard clinical procedures.

Enhancing the applicability of the suggested approach requires identifying possible generalization routes to more complicated scenarios. One approach is to carry out focused studies to evaluate the model's efficacy in a wide range of neurodevelopmental diseases other than ASD. Adding more examples of similar disorders to the dataset like Attention-Deficit/Hyperactivity Disorder (ADHD) or intellectual disabilities will help us better understand how adaptive the model is to more complex diagnostic problems. Furthermore, determining the model's generalizability requires examining its resilience across other age groups, and demographic groupings. The model's ability to generalize to complex and diverse clinical circumstances might be further improved by utilizing multi-modal data, such as genetic or neuroimaging information, and applying transfer learning techniques. These factors highlight the significance of methodically investigating and verifying the model's functionality in more complicated circumstances, offering a path for its incorporation into a more thorough framework for diagnosing neurodevelopmental disorders.

VI. Conclusion and Future Works

This study represents a major advancement in the diagnosis of ASD. A remarkable 99.12% diagnosis accuracy is achieved by using an ABC optimized RNN-BiLSTM architecture. This accomplishment highlights the potential of the suggested technique to lessen subjectivity and improve the accuracy of ASD diagnosis in addition to demonstrating its effectiveness. Clinicians can get important insights from the interpretability of the model, which enhances their comprehension of the diagnostic procedure. Moreover, this decrease in subjectivity speeds up early intervention, which is a vital component in enhancing the lives of people with autism spectrum disorders and their families. Furthermore, the elimination of subjectivity expedites the early intervention procedure, and the interpretability of the model aids healthcare practitioners in understanding the diagnostic process. Subsequent paths might entail implementing this model in therapeutic environments, carrying out extensive experiments, and broadening its relevance to encompass a range of neurodevelopmental conditions. Furthermore, investigating the possibilities of transfer learning and incorporating multi-modal data may improve diagnostic accuracy even more and increase the research's impact on the field of medical diagnosis.

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