RESEARCH ARTICLE

AI for mental health: Detection, diagnosis, and treatment of psychological disorders

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Obsessive-compulsive disorder (OCD) is a mental health state described by repetitive thoughts and behaviors. Early detection is crucial for timely diagnosis and effective treatment. Traditional diagnostic methods frequently rely on subjective clinical evaluations, which can delay intervention. Deep learning (DL) presents an innovative approach for automating OCD detection, diagnosis, and treatment planning. Many approaches have primarily focused on generalized mental health disorders, often neglecting OCD-specific detection. Limited datasets, inadequate feature extraction, and poor handling of sequential data have reduced reliability and applicability of existing detection systems. This research created an automated system capable of accurately detecting OCD symptoms while providing insights to streamline diagnosis and guide personalized treatment planning, which could bridge gap between early identification and effective clinical intervention. Sequential data of comprehensive records of some individuals diagnosed with OCD including detailed demographic data, along with clinical variables like diagnosis date, symptom duration, and prior psychiatric conditions were utilized to identify key OCD-related patterns and capture behavioral trends over time. Temporal relationships in data were analyzed to develop model performance. Redefined pied kingfisher-tuned bidirectional recurrent neural network (RPK-Bi-RNN) was designed to integrate seamlessly with diagnosis and treatment processes, providing holistic solution. RPK technique improved data representation and optimized feature selection by locating the most discriminative OCD-related patterns. Bi-RNN captured temporal dependencies in behavioral trends by processing sequential data. The results showed that the proposed system increased OCD detection accuracy with the accuracy, precision, and recall of RPK-Bi-RNN as 0.9858, 0.9754, and 0.9840, respectively. Key symptom identification also facilitated expedited diagnosis and provided useful information for customized therapy planning. The results of this study improved OCD identification, increased diagnosis and treatment process, offered useful tool for enhancing results of mental health care.

Keywords: obsessive-compulsive disorder (OCD); mental health care; diagnosis; early detection; redefined pied kingfisher (RPK); bidirectional recurrent neural network (Bi-RNN).

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Introduction

The obsessive-compulsive disorder (OCD) patients develop compulsive behaviors, disruptive impulses, and intrusive obsessions, which effectively limit one's ability to function and cause functional constraints [1]. Different patients are affected by OCD to varying degrees, as some have mild symptoms, while the others have crippling symptoms that make it impossible for them to function in relationships, at work, and in other areas of life [2]. Even though the signs of the medical illness initially appear in childhood, it is typically diagnosed in young adulthood. The high prevalence of OCD results in inadequate or inaccurate diagnoses, delaying patients' access to timely and effective treatment [3]. OCD is currently diagnosed using standardized diagnostic criteria from the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) in conjunction with clinical review. A physician's evaluation judgment and patient reported conditions are the main sources of information used in medical evaluations of OCD, which contain built-in biases together with personal perspectives [4]. Additional diagnostic methods have been integrated with the standard approaches, which consist of behavioral tests, structured interviews, and questionnaires. Research on biomarkers and brain scanning techniques currently promotes improved diagnosis methods because it reveals essential brain processes related to OCD [5]. However, the current diagnostic methods perform poorly in detecting OCD among mental illnesses, mainly because of the lack of accuracy in the results. Recent advances in artificial intelligence, particularly deep learning, have shown promise in improving mental health diagnostics by automating the detection of disorders like OCD. Tools utilizing neural networks can analyze complex behavioral patterns over time, reducing reliance on subjective clinical evaluations, which enhance diagnostic accuracy and speed, supporting early intervention. Research also emphasizes the potential of digital tools to tailor treatment pathways based on individual symptom profiles to make accurate and efficient diagnoses [6]. Real-time processing of substantial medical data allows these innovations to produce better psychiatric treatments. Contemporary diagnostic tools help physicians to detect OCD depression and anxiety, while accomplishing diagnosis tasks more quickly than conventional approaches [7]. Through automation of routine work and personalized treatment approaches, healthcare professionals achieve improved results and better service delivery structures, through which the society receives enhanced access to mental health services specifically for people who have historically lacked care and decreases public misconceptions about mental illnesses [1].

Patel *et al*. designed a neural network-based modeling using OCD class labels from hospital data and OSBs from biochemistry laboratories and found a diagnosis accuracy of 86 ± 2%, effective in OCD diagnosis *via* automation [8]. Huang *et al*. applied machine learning techniques on data from combined functional (fMRI) and structural MRI (sMRI) scans from 50 adults with OCD diagnosis with age range of 18 – 74 years old and 50 age-matched healthy controls and found that the machine learning methods had excellent diagnostic accuracy. The results showed that the method was able to characterize self-organization both within and outside the cortico-striatal-thalamo-cortical (CSTC) circuit associated with OCD with standalone models using only a single MRI metric better than the combined fMRI and sMRI model [9]. Kim *et al*. designed a full AutoML pipeline that involved separate elements of feature engineering, feature selection design, and implementation using diffusion tensor imaging (DTI) data of 1,336 adults and 317 children. The results showed that the adult AUC score was 76.72 compared to 72.45 for children. However, the study faced accuracy challenges because of a non-negligible number of variable factors due to the study site and medication [10]. Haque *et al*. used machine learning classifiers of random forest (RF), decision tree (DT), and Gaussian Naïve Bayes (GaussianNB) on a dataset with 1,474 features from the Australian Mental Health Survey and reported 91% accuracy for OCD and 79% for social anxiety disorder (SAD). Their model was promising with high classification accuracy and as a web application for early yellow-flag detection. However SAD detection accuracy was low [11]. Furthermore, Grassi *et al.* adapted a gradient-boosted decision tree model and hyper-parameter tuning on a longitudinal multicenter dataset containing 227 predictors based on 428 observations. The model showed moderate predictive ability. The study explained important predictors of OCD, but its generalizability was limited by intra-center variability and small sample sizes in some centers [12]. Farhad *et al*. proposed a hybrid 1D convolutional neural network (CNN)-long short-term memory (LSTM) deep-learning model that used EEG data to differentiate OCD patients from healthy controls. The model achieved 90.88% cross-validation accuracy, while a 1D CNN-gated recurrent unit (GRU) model had 85.91% accuracy. The study also identified significant brain regions. However, the study did not explicitly address potential limits in dataset size or generalizability [13]. Kalmady *et al*. reported a multi-parcellation ensemble learning framework (EMPaSchiz) that adopted transfer learning using factors to predict OCD diagnosis. The study used a resting-state fMRI dataset comprising 350 subjects and achieved 80.3% accuracy. This model constructed knowledge, so the learning used factors to recursively improve predictions and streamline features [14]. Bruin et al. performed a meta-analysis of resting-state functional connectivity data with 1,024 OCD patients and 1,028 controls from the ENIGMA-OCD consortium with 28 datasets. Despite using large datasets and being able to provide new information on brain connectivity in OCD, the study was unable to provide a reliable individual-level classification and did not identify reliable frontostriatal abnormalities [15].

Currently, accurate and timely diagnosis of psychological disorders in clinical settings continues to be a significant challenge due to the multifaceted nature of the symptoms, overlapping conditions, and limited traditional diagnostic approaches. Misdiagnoses and delays in diagnosing can lead to ineffective treatment, detrimental effects on the patient, and waste of financial resources. Additionally, traditional machine learning models often perform poorly on imbalanced datasets because they fail to recognize small classes, a dimension that is particularly relevant in medicine because rare diseases can be very serious. There is a critical need for reliable, sensitive, and accurate diagnostic tools for psychological disorder data. This research proposed a new deep learning (DL) model of the Redefined Pied Kingfisher-tuned Bidirectional Recurrent Neural Network (RPK-Bi-RNN) to psychological disorder diagnoses for early detection and reduced misdiagnosis by using bidirectional recurrent neural networks fine-tuned with the Pied Kingfisher optimization algorithm. The proposed model was assessed using accuracy, precision, and recall, while further comparative studies were performed with existing machine learning methods of RF and support vector machine (SVM). The proposed model would assist with informed clinical decisions potentially resulting in improved patient health and treatment efficiency. The innovative methodologies utilized in this research would provide an uncommon pathway to improved neural network implementations in many medical applications. The results provided valuable reference for future research on applying artificial intelligence to mental health diagnosis and other fields and developing intelligent medical systems.

Materials and methods

Data resource

Kaggle, a publicly accessible open-source dataset (https://www.kaggle.com/datasets/ohinhaque/ocd-patient-dataset-demographics-and-clinical-data) was employed as the data resource of this study. The "OCD Patient Dataset: Demographics & Clinical Data" was an extensive dataset of 1,500 patients who were diagnosed as OCD with 753 males and 747 females and aged from 18 to 75 years old. Ethnic representation covered African, Asian, Caucasian, and Hispanic individuals. In addition to clinical data like diagnosis date, duration of signs, and previous psychiatric diagnoses, the database also contained demographic information like age, gender, ethnicity, marital status, and educational attainment. The data was divided into 80% (1,200 cases) for model training and 20% (300 cases) for validation.

Process for improving, detecting, diagnosing, and treating OCD through AI technologies

The process began with the data collection from OCD patient datasets. The data was moved to the pre-processing stage to collect and manage missing values and encode categorical variables with label encoding before feature extraction

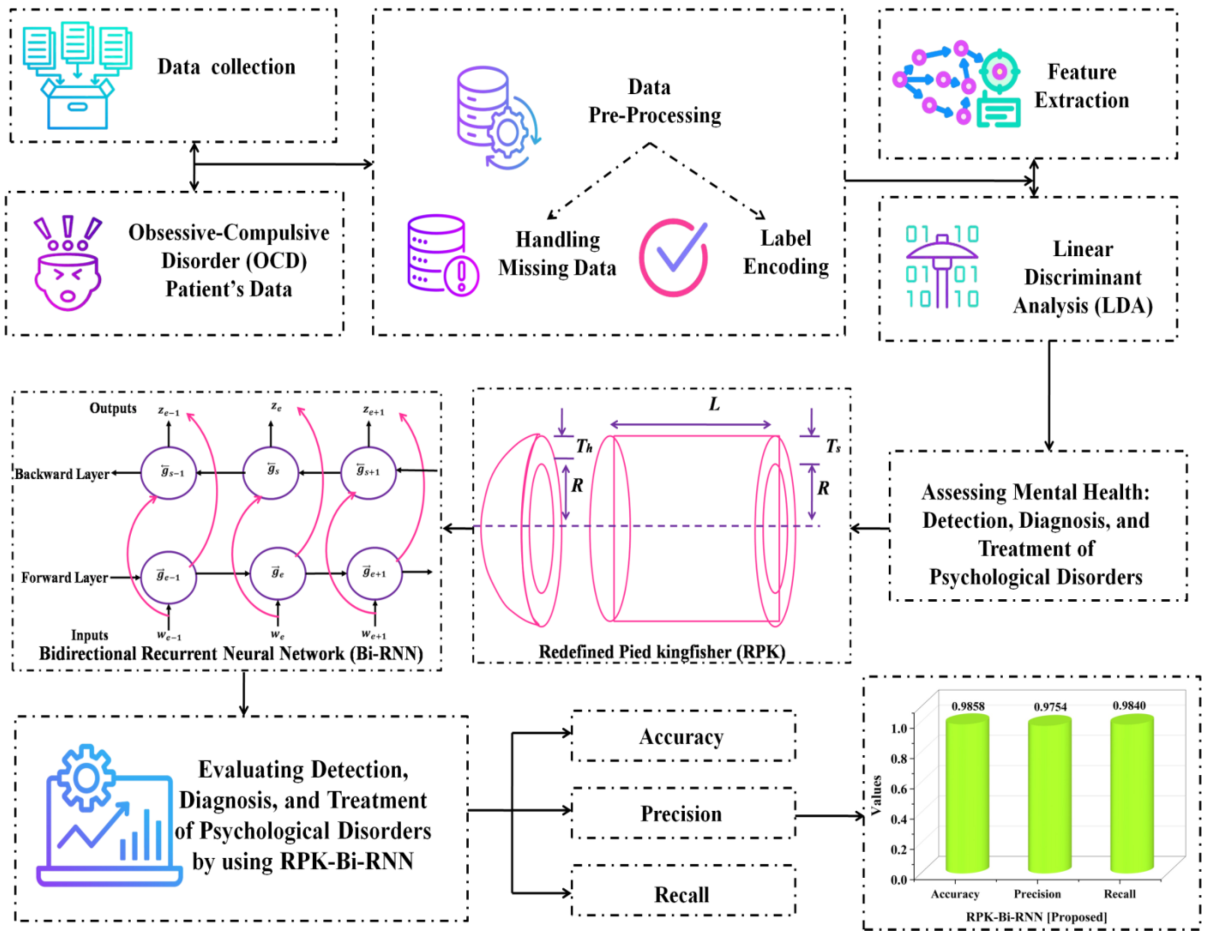

Figure 1. Flowchart of the hybrid RPK-Bi-RNN model construction.

using linear discriminant analysis (LDA) to reduce the number of dimensions, while enhancing the most discriminating features. Refined features were input into a hybrid model with an RPK optimization approach and Bi-Directional RNN (Bi-RNN) that captured temporal learning by making useful connections with past and future data. The integrated RPK-Bi-RNN model was developed to assess psychological disorders with accuracy defined by metrics on performance (Figure 1).

Data pre-processing

The data pre-processing included filling in missing data by imputation techniques and removing incomplete entries to achieve data consistency. For DL models to process data accurately, each categorical variable required label encoding that transformed such variables into numerical representations.

Handling missing data

To fix the problem that the frequent occurrence of missing values in OCD dataset hurt DL models, the information in the OCD dataset was used to compute feature central tendencies for the substitution of unobserved values to completely preserve important information. When missing information was neither significant nor substantial, the number of impacted rows or columns should be eliminated from the OCD dataset to maintain OCD data coherence. This process improved OCD dataset's precision and dependability for future prediction results.

Label encoding

Label encoding was an essential method for preparing data, particularly when dealing with categorical variables. Numerical conversion of categorical OCD data was required for the input of DL models. In label encoding, each unique category or class was assigned an integer value. However, label encoding imposed an ordinal relationship between categories that could not accurately represent the data's actual characteristics.

Feature extraction

Through feature extraction, new dimensions were created by mixing with previous dimensions. Efficacy was assessed using the outcomes of randomized testing based on classLDA that aided in the discovery of a set of basis vectors (w_k) using DL. The w_k vectors were the maximum percentage of the original instance sets inside and between-class dispersals. The generalized eigenvalue problem for finding w_k basis vectors was shown below.

$$X_{opt} = \underset{\omega}{argmax} \frac{|X^S T_D X|}{|X^S T_v X|} = [\omega_1, \omega_2, .., \omega_K] \quad (1)$$

where K was subspace's dimension. T_D was between classes, while T_v was within classes as shown below.

$$T_D = \sum_{l=1}^{b} N_l (\mu_l - \mu)(\mu_l - \mu)^S \quad (2)$$

$$T_U = \sum_{l=1}^{b} \sum_{wv \in W_l} (w_v - \mu_l)(w_v - \mu_l)^S \quad (3)$$

where b was the number of classes. W∈Q^M and W_l were samples. N_l was the number of classes in k. μ was the mean. The base vectors (w_k) that were needed in equations 1 to 3 were the first L the largest Eigen values $\{\Psi_l \mid 1 \leq l \leq K\}$ and provided that SV was not singular. As the initial vectors of LDA were perpendicular to its neighbors, it was estimated into the LDA subspace to obtain its representations by applying a simple linear technique WTx.

Redefined pied kingfisher-tuned bidirectional recurrent neural network (RPK-Bi-RNN)

A key element in establishing AI-driven OCD detection, conducting diagnostic evaluations, and customizing treatment approaches for individuals with OCD was the redefined pied kingfisher-tuned bidirectional recurrent neural network (RPK-Bi-RNN) functionalities, which allowed the identification of time-based relationships between OCD symptoms and the analysis of behavioral data from the past and future. The model was better able to recognize significant features of the pied kingfisher technique, which increased its ability to recognize patterns associated with OCD. To improve therapeutic outcomes, the system generated more accurate diagnoses and individualized treatment regimens based on patient data.

Bidirectional Recurrent Neural Network (Bi-RNN)

A bidirectional recurrent neural network (Bi-RNN) was a simple version of the typical input neural network which allowed for the modeling of sequential data. To create an AI-powered tool that provided reliable identification, diagnosis, and individualized therapy selection for OCD, Bi-RNN generated a forecast upon getting an input, modifying its hidden culture, and executing a time phase. The extremely complex concealing and inconsistent development of Bi-RNN equipped it with significant expressive ability and enabled it to keep disguised while combining OCD data at various phases and using it to make accurate predictions. Even though the flexibility of each part was rather fundamental, prolonged use produces extremely intricated patterns. The typical Bi-RNN was established by considering the sum of input arrays $(w_1, \ldots, w_S)$, a value of $(g_1, \ldots, g_S)$ calculated by Bi-RNN, a hidden significance, and output arrays as $(p_1, \ldots, p_S)$. The conventional Bi-RNN was expressed as follows.

$$g_S = \tanh\ (X_{gw} w_s + X_{gg} g_{S-1} + a_g) \quad (4)$$

$$p_s = X_{pg} g_s + a_p \quad (5)$$

Redefined pied kingfisher (RPK)

To allow the model to choose significant features while reducing noise, the RPK algorithm optimized both the exploratory and exploitative phases. By exploring the most important aspects of the data, the method improved the performance of DL models. The RPK method's versatile adaptability allowed for producing outstanding results for high-dimensional medical and psychological condition detection as shown below.

$$W_{j,i} = W_{KA} + (W_{\cup A} - W_{KA}) \times q$$

$$\mathrm{j} = 1, 2, \ldots, \mathrm{m};\ \mathrm{i} = 1, 2, \ldots, \mathrm{n} \quad (6)$$

To iteratively update the pied kingfishers' locations and develop an AI-driven system for the accurate detection, diagnosis, and personalized treatment planning for OCD, the first stage of RPK algorithm adaptively alternated based on ambient factors to detect, diagnose, and treat psychological disorders and was shown as follows.

$$W_j(s = 1) = W_j(s) + \alpha \times S \times (W_i(s) - W_j(s))$$

$$\mathrm{j}, \mathrm{i} = 1, 2, \ldots, \mathrm{M}\ \&\ i \neq j \quad (7)$$

To conduct space exploration, the pied kingfisher's position was updated at each iteration of the refined pied kingfisher optimization to develop an AI-driven system for the accurate detection, diagnosis, and personalized treatment planning for OCD. The following iteration's potential position served as a fresh candidate solution, while the RPK's current solution remained. As the program explored several locations, a randomly generated number with a normal distribution aided in the discovery of new regions to detect, diagnose, and treat psychological disorders. The degree of solution variation that members could explore was influenced by the number of people in the group. "Perching" and "hovering" were used in the pied kingfisher movement algorithm to determine the movement behavior as shown below.

$$S = (\exp(1) - \exp\ \left(\frac{s-1}{N}\right)^{\frac{1}{\pi}}) \times \cos\,(2\pi q) \quad (8)$$

The RPK controlled exploration against exploitation during search phase by modifying the parameter S using the hovering method, which combined random numbers and iteration restrictions. To maintain the best possible balance between exploration and optimization during search operations, optimization was accomplished by adjusting S as follows.

$$S = A_q \left(\frac{s}{N}\right)^{\frac{1}{\pi}} \quad (9)$$

$$A_q = \times \left(\frac{fit(i)}{fit(j)}\right) \quad (10)$$

The RPK algorithm efficiently modeled the pied kingfisher's ability to dive quickly and employed accurate bill movements to catch prey as follows.

$$W_j(s+1) = W_i(s) - G_B \times p \times \alpha \times (a - W_{best}(s)) \quad (11)$$

$$G_B = q \times \left(\frac{fit(j)}{e_a}\right) \quad (12)$$

$$p = exp\left(-\frac{s}{N}\right)^2 \quad (13)$$

$$a = W_j(s) + \sigma^2 \times q \times W_{best(s)} \quad (14)$$

Kingfishers and otters worked together to increase the efficiency of kingfishers' hunting by flushing fish out for it to catch as shown below.

$$W_j(s+1) = \begin{cases} W_n(s) + p \times \alpha \times |W_j(s) - W_m(s), if q > (1 - OF)(b) \\ W_j(s) Otherwise(a) \end{cases} \quad (15)$$

$$OF = OF_{max} - (OF_{max} - OF_{min}) \times \left(\frac{s}{N}\right) \quad (16)$$

The hybrid RPK-Bi-RNN was designed to develop an AI-driven system for accurate detection, diagnosis, and personalized treatment planning for OCD.

Validation of the proposed model

The validation was conducted on a python platform (https://www.python.org/) using an

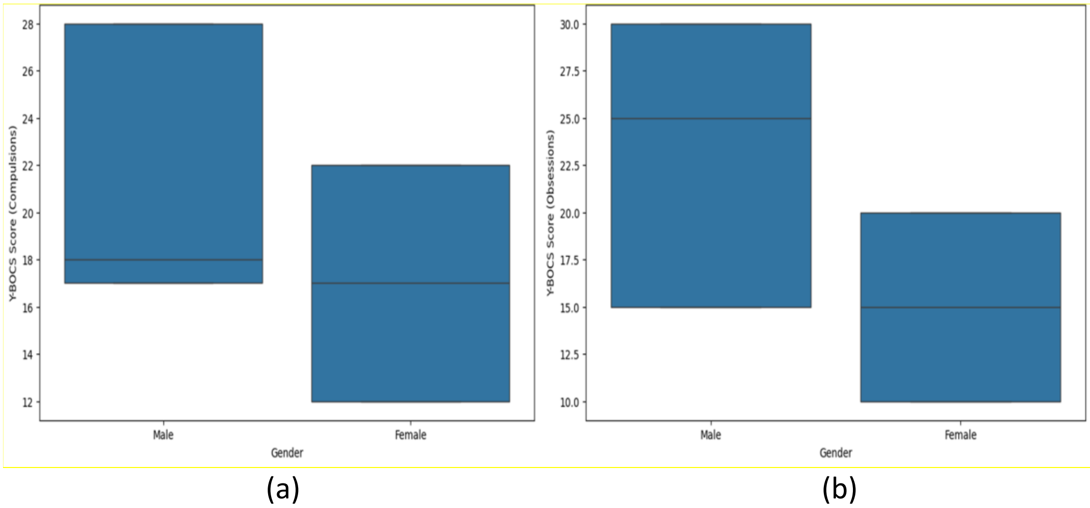

Figure 2. Graphical representation of Y-BOCS. (**a**) Compulsions. (**b**) Obsessions.

Intel® Core i9 processor laptop with 8 GB RAM and Windows 11 system. The proposed RPK-Bi-RNN model was compared with existing methods of RF and SVM [16].

Results and discussion

OCD symptoms analysis based on genders

The comparison of OCD symptoms for male and female participants based on Y-BOCS scores was conducted to assess compulsions and obsessions in this study. The results of Boxplots showed that male participants had higher median scores and more variability for both types of symptoms than females, which indicated that males had a larger interquartile range than females and more fluctuation and severity of symptoms. On the other hand, females had lower median scores and less range, indicating a more stable and milder symptom profile (Figure 2). The findings suggested that males appeared to be at a higher risk of developing severe and disruptive OCD symptoms than females, which had clear implications for the clinical assessment and treatment of patients with OCD and suggested the need for a thorough gender-sensitive diagnostic assessment and treatment plan. Understanding these differences could help improve treatment allocation and ultimately planning for mental health outcomes for both genders.

Validation of proposed model

The validation results of the proposed RPK-Bi-RNN model based on three performance metrics of accuracy, precision, and recall showed that the model accuracy was 0.9858, indicating the overall prediction performance of the model on both positive and negative classes. A precision of 0.9754 supported the idea that the proposed model could minimize false positives so that only valid cases were classified as positives. The recall value was 0.9840, which meant that the model could catch almost all the true positives that should be considered relevant when considering cases for psychological disorder risk (Figure 3). Collectively, these results demonstrated that the proposed model was fairly a balanced and reliable model to be considered for a clinical decision support system.

Comparison of the proposed model with existing algorithms

Accuracy was referred to the ratio of correct predictions that the model made across all instances of the classification of psychological disorders and represented the overall capability of the model to classify both the positives and negatives. While measuring accuracy is always

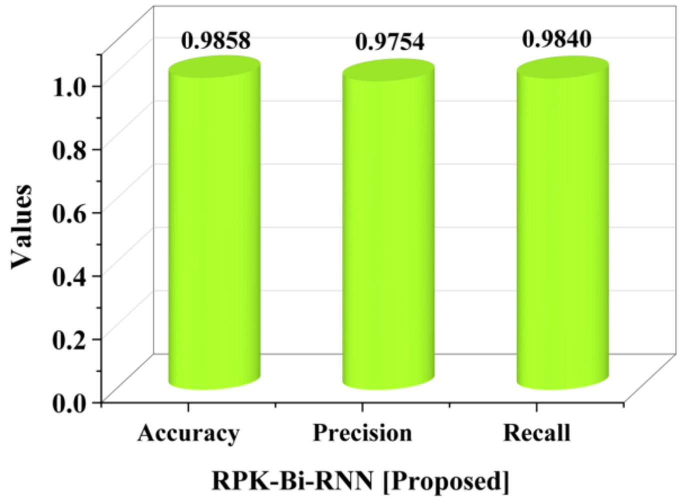

Figure 3. Validation of proposed RPK-Bi-RNN.

worthwhile, it can sometimes be misleading, especially in cases of imbalanced data where the model may fail to make accurate predictions for the minority class even if it predicts the majority class correctly. Therefore, while the model did give a general metric for performance, it should be considered in addition to other metrics. The results showed that the value of accuracy in the proposed RPK-Bi-RNN model attained 0.9858, which was higher than the existing RF method of 0.9200 and SVM method of 0.9644. Precision referred to the ratio of true positive predictions to the sum of true positive and false positive predictions made by the model, which measured how well the model prevented false positive diagnosis situations where a patient was incorrectly diagnosed with a disorder they did not have. Precision was especially important in medical diagnosis because it avoided unnecessary treatments and therefore maximized healthcare costs from false alarms. The results showed that the values of precision in proposed RPK-Bi-RNN was 0.9754, while RF was 0.9255 and SVM was 0.9676. Recall referred to sensitivity and measures the ability of the model to recognize all of the positive cases correctly, which was the proportion of true positives recognized from all the real positive cases. Recall was maximized in clinical scenarios given that missing a diagnosis (false negatives) could have serious ramifications. Even though increasing recall might increase the number of false positives, the priority was to ensure that all patients with a disorder were recognized. The value of recall in the proposed RPK-Bi-RNN model was 0.9840, which was greater than the existing methods of RF as 0.9355 and SVM as 0.9810 (Figure 4).

This research developed an AI-driven system for the accurate detection, diagnosis, and personalized treatment planning for OCD. RF model handled enormous amounts of computer work when used with extensive datasets or numerous trees in the system. The algorithm was found that it was difficult to function well with data that contained many dimensions and had few data points. RF failed to identify temporal relationships with a series of events because OCD diagnosis through behavior pattern analysis required this critical capability. During training sessions, SVM became complex when handling large datasets because of its high computational needs. Effective operation of SVM depended on precise parameter optimization, which needed significant data preparation to work effectively. Diagnostic tasks in mental health therapies required inadequate handling of time-based or sequential information because SVMs demonstrated low effectiveness in this domain.

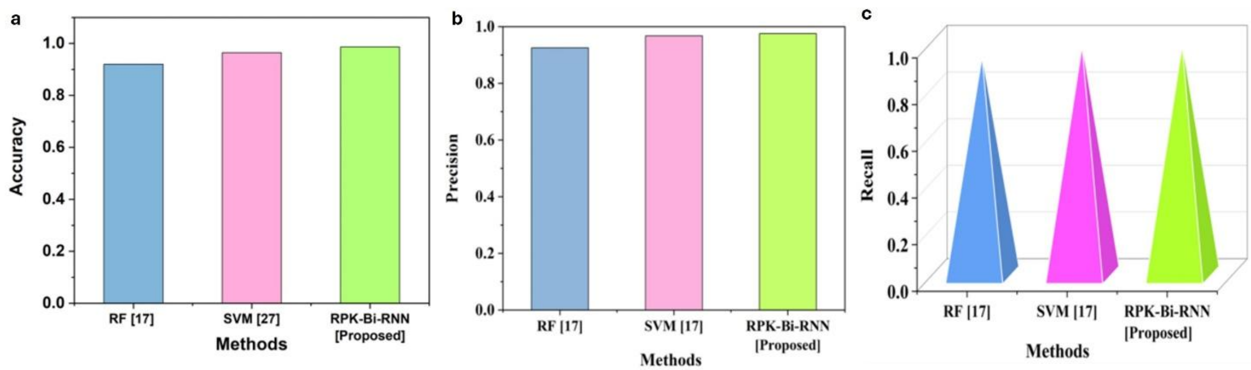

Figure 4. Comparison of accuracy, precision, recall of different models.

Mental health applications received considerable value through the proposed RPK-Bi-RNN implementation. The RPK-Bi-RNN detected OCD patterns in OCD data better because it identified both spatial elements and time-based sequences. Evaluation of sequential behavioral data using the model yielded better diagnostic precision as well as the capability to generate individual treatment strategies. The detected gender differences in OCD severity suggested that clinicians should consider gender-based factors when assessing and treating OCD patients. The incorporation of relevant gender differences could lead to more targeted and effective interventions that could reduce the impact of OCD on mental health for all genders. The proposed RPK-Bi-RNN model performed efficiently in detecting, diagnosing, and treating psychological disorders. This system analyzed clinical and demographic data and behavioral information through sequential analysis to offer precise real-time diagnoses, which helped in designing individual treatment plans for patients. The ability to detect OCD becomes hindered using limited and poor-quality datasets when it needs more extensive information about diverse patient populations for effective generalization. Future research should concentrate on enlarging available data collection efforts and refining existing feature retrieval approaches while adding multiple data modalities to improve system performance levels for clinical use.

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