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Accuracy enhancement with artificial neural networks for bipolar disorder prediction

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ABSTRACT

The perfect physical health and mental wellbeing is an important aspect of human kind. Healthcare sectors involving machine learning and deep learning is providing good healthcare services is helping people for safeguarding them from being exploited with extra and unnecessary expenditures on medical check-ups. This gives treatments and many health services on time when needed. In this paper, different performance metrics are applied on online bipolar dataset named “Theory of mind in remitted bipolar disorder dataset” from Kaggle to evaluate the diagnosis for bipolar disorder feature prediction and analysis. In this study the proposed accuracy is better as compared to previous traditional models. As a result, artificial neural networks reduce the time taken in training and classification of dataset in prediction as given in result by optimal combination of epoch and hyperperameters.

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1. INTRODUCTION

A complex brain disorder, bipolar disorder is affecting millions of people these days around the globe. The disorder has symptoms of alternate oscillations caused by patient’s mood swings between mania and depression states. These mood swings are due to different physical and psychological features. These set of behavioral changes, varying mood swings and psycholinguistic features are used for feedback analysis of patient. Mental illness like depression, anxiety, stress, restlessness, aggression and other mood related changes can affect and disturb any one in some situations, events or circumstances. This all collectively results in mental disorder which physical and emotional changes. On huge datasets, neural network-based techniques and machine learning (ML) can be used to extract pertinent data and make predictions [1]. Depending on the technology utilized and the datasets, an algorithm's results may differ. Finding the best modal for a given dataset and application is the essential specification. In this study, supervised learning is utilized to forecast disorder since the aim is known in advance. The algorithm creates a function that maps various output variables to input variables. This category includes both regression and classification modals. While the output variable in regression modals is continuous, the output variable in classification modals has two or more discrete values.

The background literature gives a brief and precise background of literature and ML methods for diagnosis of bipolar disorder. The research prepared a combined model framework which helps to classify mental health features using ML with its applications and challenges [1]–[4]. This study proposes a combination of models, the hybrid native base tree (NBTree) showed the results have better accuracy and precision as compared to the other two approaches [5]–[7]. The detection of bipolar disorder using radial bias function using neural networks [8]. A hybrid classifier with Naïve Bayes and decision tree is proposed for bipolar disorder prediction [9]. Supervised ML models are compared to study mental health detection and prediction [10], [11]. A hybrid classifier is proposed to analyze logistic regression and support vector classifier as logistic vector tree [12]. A hybrid support vector machine (SVM) model was applied to find out the distinct features and calculated high-dimensional inputs with proper accuracy [13], [14]. A classification model on logistic regression and SVM. Mental illness like depression, anxiety, stress, restlessness, aggression and other mood related changes can affect and disturb any one in some situations, events or circumstances [15], [16].

A hybrid model for detecting of depression and depression forecasting using deep learning techniques is proposed [17], [18]. This study compared the convolutional neural network-bi long short-term memory networks (LSTM) model with the existing convolutional neural network (CNN) and recurrent neural networks (RNN) with the baseline approaches [19]. Implementation of logistic regression as the best proposed model for prediction of disorder [20]. A neural network approach in offspring of bipolar disorder parents [21], a continuous monitoring of mood swings in elderly peoples using a methodology [22]. These study results that artificial neural network (ANN) is the predictive model for bipolar disorder diagnosis [23]–[25].

They proposed genetic algorithm to predict accuracy better as compared to other algorithms for the survival of heart attack failure patients [26]. They combined CNN technique to enhance feature extraction and classification accuracy and a classification with CNN to identify dysgraphia in children having accuracy of 91% [27], [28]. The proposed Alzheimer's disease-3 deep CNN (AD-3DCNN) model has highest accuracy for predicting different stages of AD as compared to other existing models [29]. Designed a model which includes an automatic feature extractor, modified hidden layer and activation function [30]. The paper focus on automatic detection of strabismus using deep neural models according to different image acquisition [31]. They develop an architecture for CNN by combining steps of genetic algorithm for automatically detecting autism [32]. Designed an approach for early detection of Parkinson's disease using speech features by RNN with LSTM to improve the classification performance [33]. They proposed that bidirectional RNNs give better results than unidirectional in cardiac disorder prediction [34]. A study on animal simulation with NARX RNN to record their neuron activities [35]. A 2D-CNN deep learning model is used to detect cardiovascular issues in 17 annotated categories of long-term electrocardiograms [36]. The study gives a solution for detection of insomnia sleep disorder using biomedical sensors having internet of things which results to be more cost effective and less time consuming [37].

The novel contributions of our study, an improved ANN model to optimize and improve the prediction accuracy of bipolar disorder accuracy in patients by choosing an optimal combination of epoch and hyperperameters on online bipolar dataset named "Theory of mind in remitted bipolar disorder dataset" from Kaggle. The research includes:

- Design a bipolar disorder prediction accuracy model using ANN for diagnosis.
- For optimization of hyper parameters of neural network like activation function, layers of neuron, batch size, accuracy, loss, batch size, and epoch using grid search and random search method.
- Result validation by training and testing validation and 10-fold cross validation method.
- A learning insight to how ANN affects prediction accuracy on the dataset.
- Using several parameters compare the model performance with epoch and hyperperameters.

2. METHOD

The methodology gives an analysis of how deep learning techniques are used in detection of bipolar disorder. This section shows how the research methodology is performed on the dataset using deep learning model and the flowchart to predict the bipolar disorder. This is subdivided in five sections, data acquisition, data pre-processing, parameterisation, model selection, optimal combination of hyperperameters as given in flow chart.

2.1. Dataset acquisition and preprocessing

The dataset taken into consideration is an online bipolar dataset named "Theory of mind in Remitted bipolar disorder dataset" from Kaggle recorded from a device MiniPons, which uses interpersonal accuracy to record patient's values on different attributes. The data is recorded on regular basis to compare the accuracy of the inputs for both mentally ill and controlled patients. The flow chart for the methodology is summarized as shown in Figure 1. The bipolar disorder disease prediction model has following steps. Data acquisition is the collection of raw data of the patients having high chances of being diagnosed with or without bipolar disorder.

Data is recorded using MiniPons which is utilized as a computational input. Enhancing the performance of the dataset can be ensured by pre-processing the dataset and is a crucial step in the data mining process. Pre-processing of the attributes from the 12 different attributes mentioned in the dataset such as group, age, type, body video, dominant, submissive, negative valence, positive valence, face video, combined channel, audio prosody and right answers has been processed and analyzed.

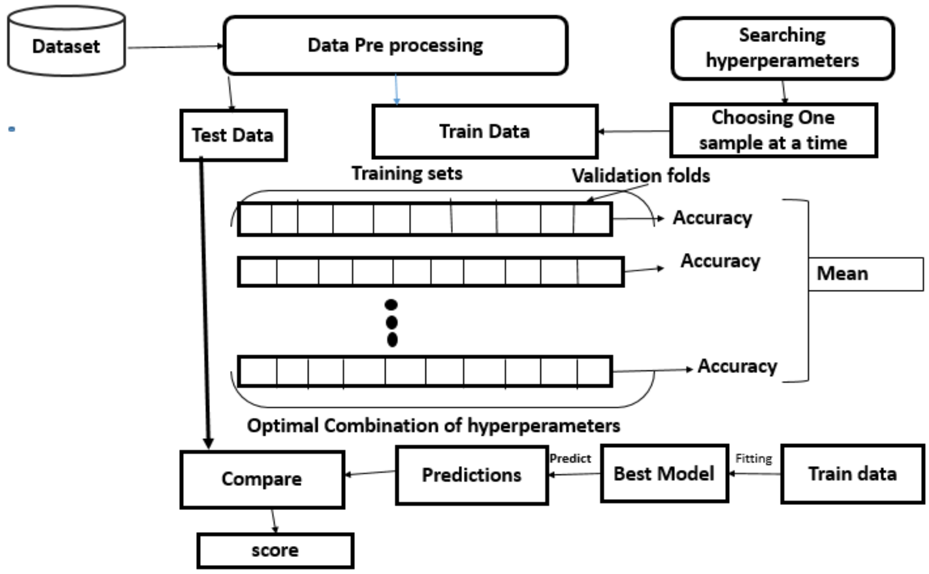

Figure 1. Flowchart for disease prediction

2.2. Parameterization of regression function for data analysis

Selection of modal has many approaches, one of which is regression. Regression is a fundamental problem in deep learning, which appears for many range and diversity of research applications including robotics, time series analysis, optimisation, image processing, video animation, automatic video annotation. To find a regression model requires a variety of selections which includes the following:

- To choose the model and its type as well as parameterization of regression function.
- Finding loss or objective function.
- Overfitting and model selection.
- Relationship between loss functions and parameter priors.
- Optimal combination of hyperperameters.

Given a data set $S = \left\{ \begin{matrix} xj, yj \\ p\wedge \end{matrix} \right\}$, design an ensemble model by (1):

$$\sum tp(xj) = y\, j \tag{1}$$

where xj is the input vector and yj is the predicted output. For a dataset, function classes are good candidate to model the data and to choose the particular parameters. The ML modals are implemented busing the statistical and data visualization tools. For the feature evaluation of patients, a validation method of 10-fold cross validation is used. To validate each fold, 75% of the patients are used for training the data and the remaining 25% are used to test and validate. Finally, when the database was created, the implementation of ML modals was carried out. The modal selection on the basis of performance allows us to compare various models and to figure out the best modal that explain the training data reasonably and in a concise manner. If a regression model is given by (2).

$$g(x|\theta), \tag{2}$$

Loss function θ*=arg min E(θ|x), then the model parameters loss or objective functions, optimization that determine the good or best fit modal which allow us to reduce the loss as given in (2). The probabilistic models are mainly induced and motivated by loss function and optimization. The hyper-parameters used in ML techniques often have one or two values that are adjusted specifically for the algorithms during training. These hyper-parameters' various characteristics like activation value, kernel value, and no of folds. To achieve the best performance, these parameters in each technique lead to algorithms with varied prediction performances. Each method is train by Bayesian optimization approach to estimate the configuration of hyper-parameters to improve the performance of algorithm. This aims at relationship between different hyper-parameters and their performance achieved by the algorithms. The basic approach of ML model is to generalize from examples the degree of knowledge regarding the training task performed. Some ML models uses generalization framework for which they describe the knowledge structure in an underlying manner. A model with high variance over fits the data because it learns too much from the training set of data while a model with high bias is constrained by genuine trends and under fits the data because of this. The ideal model possesses qualities that fall between the two. Validation curve finds the sweet spot between under fit and over fit that can generalize the model. The best suited validation curve is a one which plot the function of model's error that controls the models tendency to over and under fit the data.

2.3. Structure of artificial neural network model

ANNs are deep learning supervised models similar to our brain. ANN is the model that simulates human brain neurons. ANN structures get their inspiration from the functioning of our nervous system, allow the designs to process information in a manner similar to that of our biological brains. As a result, they can be used as tools to address issues like facial recognition, which our blood brain can handle with ease. They are used for regression to learn non-linear relationship among target and features because of the mathematical activation function in layers to find the output of a neuron. A typical structure of ANN has 3 layers input layer, number of hidden layers and output layer. Inputs are given to first hidden layer and last hidden layer gives the output. In an ANN, each node in the hidden layer receives input from the input layer before it is sent to each node in the output layer. We need to be cautious while passing before they ultimately arrive at the output layer because there may be a lot of nodes per layer and multiple hidden layers are also there. Each layer has n number of neurons and an activation function associated with each neuron. This function is responsible for non-linearity in the relationship. Each layer has regularizes associated with it which are responsible for preventing overfitting. This has input layer, neuron and output layer layers of network are artificial neurons like us biological brain having weights assigned to them. This is trained using backward propagation to modify the predicted and actual weight as the modified weight. This modified weight is given to testing using forward propagation. In this way error is minimized and an output close to target value.

If the given inputs are X1, X2, X3, …, Xn. The associated weights with inputs are w1, w2, w3, …, wn. Then the weighted inputs are given as (3):

$$\sum_{i=1}^{n} \mathrm{Xi} * \mathrm{Wi}^{n} \tag{3}$$

the activation function is applied as (4):

$$\varnothing\left(\sum_{i=1}^{m} \mathrm{Xi} * \mathrm{Wi}^{n}\right) \tag{4}$$

there are two phases of artificial neural network:
- Forward propogation.
- Backward propogation.

The process of multiplying weights with each feature and adding them with bias is called forward propagation whereas the process of updating the weights in the model is backward propagation which requires optimization and loss function [27]. The output of neuron is the sum of all the values of neuron in the previously connected layer [29]. We have developed a neural network for the prediction of disorder, the related attributes of mentally ill person are given to the first layer, then it is given to first hidden layer and gives a weighted value to analyze the data, the weighted sum of hidden layers is passed to output layer to give the resultant output using sigmoid activation function. Sigmoid activation is an activation function used in deep learning models which is a S-shaped curve shown in Figure 2. This transforms a sigmoid value between 0 and 1. In ANN, this is used as activation function in neurons to introduce non-linearity in the model and to explore complex decision boundaries. Function is used in different applications like image recognition, natural language processing (NLP) and speech recognition. Sigmoid function is given mathematically as (5);

$$f(x) = \sigma(x) = 1/1 + e^{x} \tag{5}$$

sigmoid derivative is given as (6).

$$f'(x) = \sigma(x)\big(1 - \sigma(x)\big) \tag{6}$$

Table 1 shows the description of our ANN model. To train the network, weighted connections are initialized in a random manner, it proceeds with the input data to generate the output. This generated output is compared with the actual output and the value of error is calculated in (7).

$$\text{Binary Cross Entropy } LBCE = -1n\ \Sigma(yi \times log(\hat{yi})) + (1-yi)\ ni=1 \times log(1-\hat{yi}) \tag{7}$$

The binary cross entropy is given by binary cross entropy loss (LBCE). n is number of samples, y and y' are actual and predicted result output. This error calculated is given back by backward propagation to the network to adjust the weights in (8).

$$\Delta wij = -\eta \partial Error \partial\ wij \quad (8)$$

Where Δwij – weight change, and η – learning rate. Once all the weights are updated the output is again calculated until the minimum possible error is calculated.

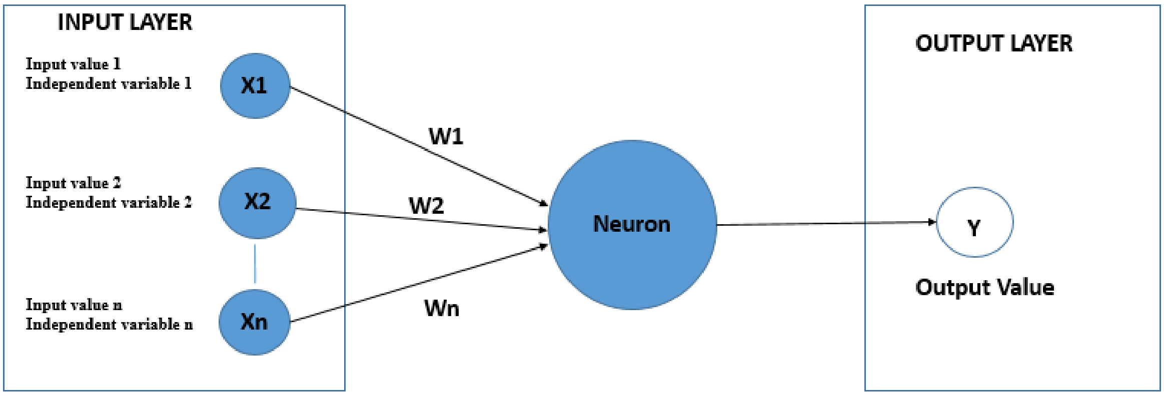

Figure 2. Structure of a neuron

Table 1. Description of the ANN parameters

Layers	Units	activation function	Kernels
Input (dense)	5	Relu	Normal
Hidden layer1	5	Relu	Normal
Hidden layer2	5	tanh	Normal
Output (dense)	1	Relu	Normal

2.4. Hyperparameters tuning parameters for cross validation

After processing the entire dataset on the basis of these 12 attributes, it has been further classified to training model and testing model for further performance evaluation with a ratio of 75:25. Hyperparameters of a network are appropriately configured for improving its performance. These are parameters of a model which can be set manually while creating a model but cannot be trained. Random and grid search methods are used for optimization of neurons, input layer, hidden layer, activation function and learning rate.

For improving the performance and tuning the model, 1 10-fold cross validation is used [29] along with search. This can be done with an optimization technique to get the best combinations of hyperparameters as shown in Table 2. One sample of combination of hyperparameter is used at one time. Each accuracy is calculated and an average of these was stored. Once all the possible combinations of hyperparameters are considered, the best possible combination is given as the optimal solution

Table 2. Hyperparameter tuning best configuration

Hyperparameter	Value
Inputs	11
Hidden layers	2
Activation function	ReLu
Learning rate	0.001

3. RESULTS AND DISCUSSION

The research follows the basis to improve the accuracy and prediction of diagnosis whether the patient have bipolar disorder or a controlled patient using a neural network regression model. The result calculated for the proposed model is done through performance metrics. The performance is based on the accuracy of correct observations and its relevance from the data point. The number of True positives in test data and harmonic mean of recall and precision values. Theses all can be given as:

- Accuracy: accuracy helps to calculate the percentage of correct observations out of total observations.
- Precision: precision helps to calculate the relevant number of data points from the test data.
- Recall: recall helps to calculate no. of true positives with respect to total no. of observations.
- F1 score: this is used to measure the harmonic mean between recall and precision values.

Considering these above mentioned four fundamental classification metrics, performance evaluation is done for the ANN and Table 3 shows the following performance. For this an ANN is deployed, optimised by Fine tuning of hyperparameters which includes input layer, hidden layers, activation function and rate of learning. After the validation process the performance of hyperparameter value combinations and the best combination is chosen. Hyperparameters used in analysis are; Batch_size=[5,10,15,20] and Epoch_list=[50,100,150,200,250,300]. After applying grid search, the best parameters obtained are total time taken 2 minutes. Grid search best parameters {'Optimizer_trial': 'rmsprop', 'batch_size': 10, 'epochs': 10}.

Table 3. Performance metrics of ANN model

Parameter	Artificial neural network
Precision	0.866397
Accuracy	0.858000
Recall	0.849206
F1 Score	0.857715

To evaluate and keep track of the training and validated test data, the accuracy and loss parameters were used in each epoch. Figure 3 shows the record of each accuracy and loss for each metrics. Training accuracy and validated test accuracy follows a similar increasing pattern until reaching a minimum percentage and then they stabilize. On the other hand, training loss reaches a certain percentage where it remains stable and validation test loss follows the same behavior as training loss.

Additionally, an inline graph as shown in Figure 4 is plotted to show that when batch size is 15 and epoch is 50 the accuracy is best and compared to other hyper parameters as shown in Table 4. ANN are essentially used to evaluate the model's ability to predict bipolar states. The results show that the ANNs are better than other models employed in earlier discoveries, which can be utilized to increase the precision of disease prediction. By in-creasing the training and test parameters from the dataset, the model will be improved. The model training is done to evaluate the performance of model, based on these predicted feature F1-score, recall, recall and precision.

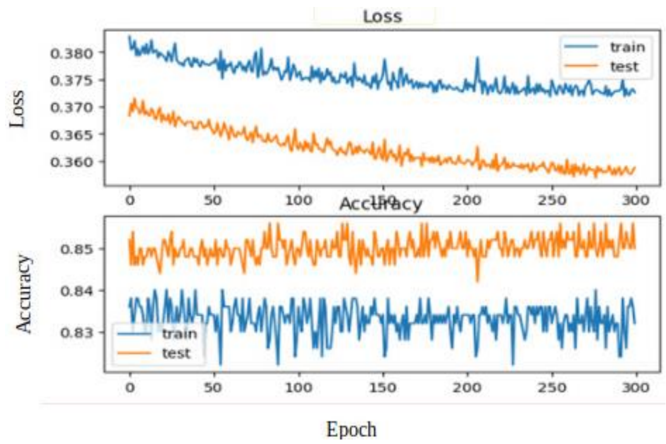

Figure 3. Loss and accuracy graph for ANN

Table 4. Calculating mini-batch accuracy and loss

Epoch	Iteration	Mini-batch accuracy (%)	Mini batch loss
1	1	83	0.3728
50	50	85	0.3525
100	100	83.8	0.3686
150	150	84.6	0.3682
200	200	83.8	0.3524
250	250	83.8	0.3532
300	300	83.8	0.3518

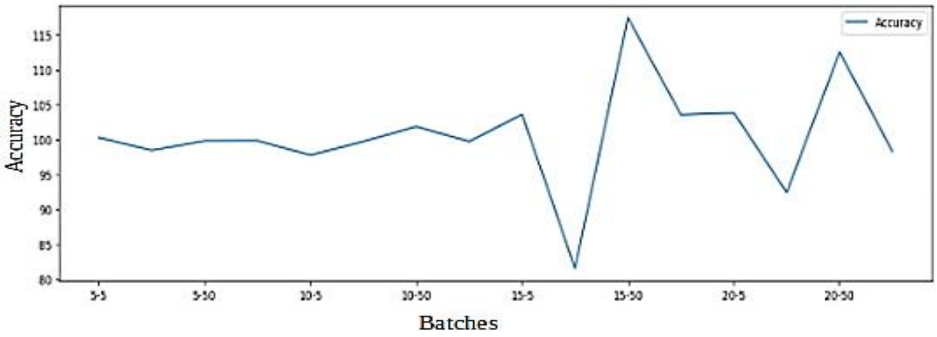

Figure 4. Inline plot of accuracy with parameters

4. CONCLUSION

With the increasing cases of people suffering from mental health issues, correct diagnosis and treatment within the time period to avoid worse health conditions of the patients. ML models in today's scenario helps to get better results within stipulated time period and is more secure as compare to cloud systems with patient's data and transaction concerns. To propose optimal detection and prediction of patient's condition with increased precision and framework productivity using ANN algorithms. Deep learning model ANN provides better results with more precision when compared to ML model and can be further used by clinicians for future reference.

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