Detecting Postpartum Depression Stages in New Mothers: A Comparative Study of Novel LSTM-CNN vs. Random Forest

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Abstract: A Novel long-short term memory with convolutional neural networks (LSTM-CNN) is used to predict postpartum depression and compared it with Random Forest (RF) Algorithm. Materials and Methods: For this research two groups were taken: The Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) and for comparison the Random Forest (RF) Algorithm was considered. After careful consideration each with a sample size of 20 to help in this research. Results: The outcomes of the study are shown in the following table (LSTM-CNN). The mean accuracy of the LSTM -CNN is 77.75% and the Random Forest (RF) Algorithm model is 72.12%, respectively. The significance of the Independent sample t-test is evident with a p-value of 0.04 ($p < 0.05$), underscoring the statistical significance of the comparison between the LSTM-CNN model and the Random Forest algorithm in the study. Conclusion: The LSTM-CNN technique outperformed the Random Forest (RF) Algorithm and other machine learning algorithms in terms of accuracy, and deep learning algorithms have generally showed promise in the prediction of Postpartum depression.

1 INTRODUCTION

Artificial intelligence (AI) has the potential to help in various ways when it comes to postpartum depression (PPD). AI can help predict which women are most likely to develop PPD and provide targeted interventions to prevent or minimize the severity of the condition. By analyzing data from various sources, including demographics, medical history, and social determinants of health, In order to give women who are at high risk of PPD preventive measures, healthcare professionals can identify them using AI algorithms (Liu et al., 2023). There are several apps available that can help new mothers assess their risk of PPD and provide information on symptoms to look out for. Some apps can even provide a diagnosis based on self-reported symptoms, although it's important to note that a professional diagnosis is typically required for treatment (Wisner, Parry, and Piontek 2002) Deep learning is extensively used in computer vision applications such as object recognition, image segmentation, face recognition, and object detection and is used in NLP tasks such as language translation, sentiment analysis, speech recognition, and chatbot development (Xu and Sampson 2022)(Padma, S et al. 2022). Deep learning is utilized in the healthcare industry for a variety of activities including disease diagnosis, drug discovery, and medical picture analysis and The recognition of speech and images is made possible through machine learning. Fraud detection systems can act fast to stop fraud by using machine learning algorithms that can be trained to recognize patterns of behavior that point to fraud (G. Ramkumar et al 2022).

There are 447 publications on work done in postpartum depression and machine learning and 11 IEEE Xplore publications that discuss postpartum depression with the advancements of machine learning. Research shows that the dataset validation provides more accuracy for early detection than other individual classifiers already in use. Nowadays data mining and Machine learning plays a vital role in detecting depression. From past research various factors can impact the likelihood of developing PPD, and analyzing tweets from diverse populations can help to identify those who may be at higher risk. By

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reaching the conclusion that machine learning algorithms possess the capacity to analyze extensive datasets, effortlessly carry out intricate computations on these data, and deliver predictive or insightful outcomes, previous studies (Saqib, Khan, and Butt 2021) have demonstrated the capability of machine learning algorithms in handling substantial data volumes and generating meaningful predictions or informative results.

Research has shown that various factors can impact the likelihood of developing PPD, and analyzing tweets from diverse populations can help to identify those who may be at higher risk (Zhong et al. 2022) Due to the broad purpose nature of most sentiment analysis techniques and their potential inefficiency when used in contexts like healthcare or finance, this research gap was discovered in the current system. There is a need for tools that can integrate domain-specific knowledge and language to provide more accurate sentiment analysis results (Yonkers et al. 2001). The primary goal of the research is to create a sentiment analysis model that would combine and evaluate sentiments from all domains. The research team focussed on building a sentiment analysis tool for the society that will improve the accuracy and effectiveness especially in more complex contexts (Thurgood, Avery, and Williamson 2009).

2 MATERIALS AND METHODS

The research took place in the Saveetha School of Engineering's Data Science lab at the Saveetha Institute of Medical and Technical Sciences in Chennai. After the datasets were gathered, preprocessing and data cleaning methods were carried out to remove any irrelevant or extraneous information. The hardware to build this model CPU was: processor Intel Core i3, 4 GB of RAM, and a 500 GB hard drive. The Sentiment140 dataset is a collection of tweets that allows you to discover the sentiment of a brand, product, or topic on Twitter (Dutta and Deshmukh 2022). Originally, tweets in this dataset were classified according to their emoticons; for example, tweets with joyful emoticons were classified as positive, while tweets with sad emoticons were classified as negative The research work was conducted on 2 groups of samples size 20 each (Iqbal, Chowdhury, and Ahsan 2018). This model was run on Windows 10 and Jupyter notebook. Table 1. shows a snapshot of the benchmark Sentiment140 dataset that was used to analyze the early markers of Postpartum Depression and how deep learning algorithms have improved the accuracy.

Novel Long-Short Term Memory with Convolutional Neural Network Algorithm

When combining LSTM with CNNs, the input data is first processed by the CNN layers to extract relevant features from the data. The output of the CNN layers is then fed into the LSTM layers, which process the sequence of features and capture temporal patterns in the data. To grow the classifier precision and decrease the presence of noise and carry out a characteristic choice (Dadi et al. 2020). In place of using complex semantic evaluation, a concept is uniquely identified via hashtags contained in the emotion tweet, particularly, the metadata tags that are used in Twitter to suggest the context or the flow of a tweet (Anokye et al. 2018). Table 6. shows the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM- CNN)

Random Forest Algorithm

The Random Forest algorithm is widely employed in machine learning for classification tasks, Algorithm, and other tasks. It uses an ensemble learning technique to merge various Random Forests to build a more reliable and accurate model. Here's how the Random Forest algorithm works:Data preparation: First, training and testing sets are created from the data. The testing set is used to assess the model's performance once it has been built using the training set. These Random Forests are constructed using a process called "recursive partitioning," which involves repeatedly dividing the data into smaller and smaller subsets depending on the most crucial qualities. Selecting the best split: At each split, the algorithm selects the best feature and threshold value to split the data. This is done by calculating the information gain or Gini impurity of each feature and selecting the one that provides the most useful information for separating the data into the target classes. For classification problems, the most common method is to use a majority vote, where the class with the most votes across all the trees is selected as the final prediction. The average of all the individual tree forecasts is frequently used as the final prediction in algorithm problems. Considering the model: Finally, the model's performance in terms of accuracy and generalization is assessed using the testing set. In doing so, metrics like accuracy, precision, recall, and F1-score are computed by comparing the projected values to the actual values.

Statistical Analysis

Data analysis, data management, and data visualization were all accomplished using IBM's

Statistical Package for the Social Sciences (SPSS). Accuracy values for both the independent and dependent variables are enhanced by the former's unique characteristics, which aid in making accurate predictions of the former's n values.The G-power of 80%, and a maximum allowable error of 0.05. SPSS has a number of features, including data analysis, assumptions, and predictive models.

3 RESULTS

The dataset is displayed in Table 1 for different backgrounds and locations. The simulated accuracy analysis of the Random Forest (RF) algorithm and Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) is shown in Table 2. For the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) and the Random Forest technique, respectively, the mean values are 77.75% and 72.12%, and the standard deviations are 4.9 and 5.1, respectively.The comparison between the LSTM-CNN model and the Random Forest algorithm is statistically significant, as indicated in Table 4 by the independent t-test significance value of p=0.04(p0.05). Figure 1 depicts the analysis of a bar graph based on the effectiveness of two algorithms. The mean efficacy of the Random Forest technique is 72.12% and 77.75% for Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN), respectively.

According to the results, the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) is a more effective method than the Random Forest one. The suggested algorithm's mean accuracy for the graphed representation is 72.12% and 77.75%, respectively.A comparison of the Random Forest method and the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) algorithm is shown in Figure 1. Table 5 displays the novel LSTM's convolutional neural network pseudocode.

Table 1. Snapshot of the Sentiment140 Dataset.

ItemID	Sentiment	SentimentSource	SentimentText
1	0	Sentiment140	is so sad for my APL friend.............
2	0	Sentiment140	I missed the New Moon trailer...
3	1	Sentiment140	omg its already 7:30 :O
4	0	Sentiment140	I was suposed 2 just get a crown put on (30mins)...

Table 2. Accuracy(%) of Novel Long-Short Term memory with Convolutional Neural Networks is compared with Accuracy(%) of Random Forest Classifier .

S.NO	Accuracy(%)of Novel LSTM-CNN	Accuracy(%)of Random Forest Classifier
1.	82.90	79.87
2.	76.79	76.00
3.	80.99	73.09
4.	79.09	71.09
5.	73.89	65.69
6.	81.00	72.08
7.	70.78	62.80
8.	68.00	69.09
9.	78.09	70.80
10.	81.09	77.09
Accuracy	77.75	72.12

Table 3. Mean, standard deviation and error mean of Random Forest and Novel LSTM- CNN algorithm.

	groups	N	Mean	Std.Deviation	Std.Error mean
Accuracy	LSTM-CNN	10	77.7500	4.91859	1.55539
	RF	10	72.1200	5.16027	1.63182

Table 4. Independent t- test has a significance value p=0.04(p<0.05) indicating the study between the LSTM-CNN model and the Random Forest algorithm is statistically significant.

Independent T- Test										
Levene's test for equality of variances							T-TEST for equality of means			
		F	Sig.	t	df	Significance (2-tailed)	Mean Difference	Std.Error Differences	95% confidence of the difference	
									lower	upper
Accuracy	Equally Variance Assumed	.002	.969	2.441	18	.04	5.00200	2.25435	.76579	10.25821
	Equal Variance not Assumed			2.441	17.959	.04	5.00200	2.25435	.76579	10.23899

Table 5. Pseudocode for Novel LSTM with Convolutional Neural Network (CNN).

a: Input data with shape (num_samples, max_seq_length) b: Target labels with shape (num_samples, num_classes)
1.Normalize and perform data augmentation on the input data -Create two ImageDataGenerator objects to normalize the training and validation data
2. Define the convolutional neural layers: -Define input shape for the model with shape (max_seq_length,) -Define an input layer for the model with the defined input shape
3. Apply the embedding layer to the input layer
4. Define a convolutional layer with num_filters filters, kernel size of kernel_size, and ReLU activation
5.Apply the convolutional layer to the output of the embedding layer
6.Define a max pooling layer with pool_size pooling window
7.Apply the max pooling layer to the output of the convolutional layer
8.Define LSTM layer with lstm_units units and dropout rate (0.2)
9.Apply the LSTM layer (with 128 units) to the output of the max pooling layer
10. Define a fully connected output layer with num_classes units and softmax activation
11. Define the LSTM-CNN model with the input layer and output layer

12. Compile the model. Prediction measure is Accuracy.
13.Train the model for num_epochs epochs with batch size of batch_size: -Randomly shuffle the data -Split the data into batches of size batch_size -For each batch, do the following: -Compute the gradients of the loss with respect to the model parameters -Update the model parameters using the optimizer

Table 6. Pseudocode for Random Forest.

Input: Sentiment140.csv
1.Start by selecting a random sample of the training data.
2. For each tree in the forest: -Randomly select a subset of features to use as input for that tree. - Using the selected features, build a Random Forest model on the subset of data.
3. Once all the trees have been built, predictions are made by taking the average prediction of all the trees in the forest.

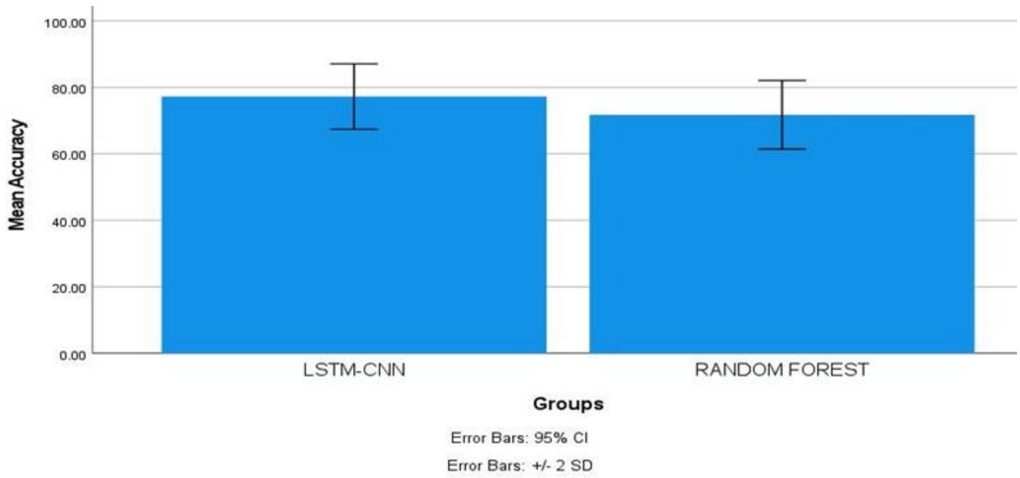

Fig. 1. Bar graph analysis of the Random Forest algorithm and Long-Short Term Memory (LSTM-CNN) algorithm. A graphical representation shows a mean accuracy of 77.75 % and 72.12% for the proposed algorithm, respectively. Random forest vs. Long-Short Term Memory (LSTM), Y-axis: mean precision +/- 2 SD.

4 DISCUSSION

LSTM -CNN has helped achieve a better accuracy(77.75%) when compared to Random forest Algorithm which achieved a lower accuracy (72.12%). The comparison of the Novel LSTM-CNN with the Random forest Algorithm (Xin and Rashid 2021) shows that the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) is better than the Random forest Algorithm. The Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) has an accuracy of 77.75 % and Random forest Algorithm is 72.12 % showing that the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) is better than the Random forest Algorithm. The two-tailed test has a significance value p=0.04 ($p<0.05$) indicating the study between the LSTM-CNN model and the Random Forest algorithm is statistically significant. As a result of the discusses and conclusions above, by concluding that the Novel Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN) appears to perform and be more accurate than the Random Forest Algorithm in all circumstances. The Bar graph analysis seen in Fig. 1 shows the Novel

Long-Short Term Memory with Convolutional Neural Networks (LSTM-CNN)

The positive effects of using a combination of LSTM and CNN can make the model more robust to noise in the input data. LSTM-CNN can be scaled up to handle large amounts of data and complex tasks. The negative effects of (LSTM-CNN) is a computationally expensive model (Karmiani et al. 2019) due to the high number of parameters, which can make it difficult to train and deploy on low-resource devices. In order to prioritize input, the LSTM-CNN employs a sigmoid neural net layer (Ifriza and Sam'an, 2021). The gates safeguard and regulate information flow, resolving the vanishing gradient issue with typical RNNs (Tan and Lim 2019). The algorithm utilized, which is based on stochastic gradient descent (Nikmah et al., 2022), aids in enforcing consistent error propagation (neither bursting nor disappearing) through its internal units. When working with large datasets, the use of LSTM models might be computationally expensive (Nikmah et al. 2022).

The LSTM-CNN is a complex architecture that requires a large amount of computational resources and training data. This makes it difficult to implement and train on smaller datasets or less powerful hardware. LSTM-CNN is built to handle long sequences, however because of the vanishing gradient problem, it can still have trouble with extremely long sequences. This happens when the weights' gradients during backpropagation shrink too much, making it challenging to update the weights and gain insight from the data. LSTM-CNN requires large amounts of labeled training data to achieve good performance. This can be a limitation in applications where labeled data is scarce or difficult/expensive to obtain. The future scope of the Novel LSTM-CNN is vast and varied, with potential applications in diverse fields and can be used to analyze speech patterns and detect changes in tone (Thurgood, Avery, and Williamson 2009; Stewart and Vigod 2016), pitch, and other vocal characteristics that may indicate depression. The Novel LSTM-CNN can also be used to analyze facial expressions and detect changes in emotion that may indicate depression. The Novel LSTM-CNN can be used to analyze EEG signals and detect abnormalities that may indicate depression. As a future work other datasets like the Multimodal Dataset for Mental Health Analysis (MMDMA),(Thurgood, Avery, and Williamson 2009; Stewart and Vigod 2016) that incorporate a wider range of modalities such as physiological signals, audio, and video recordings in addition to text can be used for depression prediction.

5 CONCLUSION

In this research work, it was possible to develop a reliable and accurate ML model that can accurately predict Postpartum depression. The Long Novel Long-Short Term Memory with Convolutional Neural Networks (77.75%) is more accurate when compared with Random Forest Algorithm (72.12%) for predicting depression of new mothers through social media.

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