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Machine Learning and Deep Learning Methods for the Identification of Depression

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ABSTRACT

Depressive disorder is a mental illness defined by persistent melancholy, pessimism, and loss of interest in once pleasurable activities. The first step in detecting depression is making a diagnosis of the disorder. Because depression may have a profound influence on a person's quality of life, early detection is key to successful treatment and better health in general. In deep learning, a subfield of AI and ML, models the human brain's architecture and function to train artificial neural networks to mimic its behaviour and make predictions. Its analysis of text, audio, and pictures, among other data sources, is crucial in the detection of depression. Computers may learn and make judgements autonomously using a kind of artificial intelligence known as machine learning. This is accomplished by the analysis of data patterns and linkages, which enables computers to continuously improve. Depression may be detected by machine learning by examining trends in several types of data, including language, tone, or behavioural indicators. Computer programs may foretell if a person will suffer from depression by analysing massive datasets. Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests (RFs), Logistic Regressions (LRs), and Naive Bayes (NBs) are some of the Machine Learning and Deep Learning techniques used for depression detection.

Keywords: Depression Detection, Machine Learning, Random Forest, Naive Bayes, Support Vector Machine, Convolutional Neural Network, Recurrent Neural Network

1. INTRODUCTION

Detecting depression is looking for and evaluating symptoms that a person may be experiencing depression. Various ways are used to detect indications and symptoms of this illness in people. These methods range from more current approaches employing machine learning and deep learning algorithms to more classic approaches like clinical exams and self-report questionnaires. Social media, text messages, and physiological indications are just a few of the sources that advanced computers sift through to find patterns linked to sadness. These algorithms are able to deduce a person's mental health state from their language, emotion, and behaviour patterns. Early intervention and assistance for those suffering from depression may be made possible by this technological innovation, which might improve people's well-being in the long run.

Machine learning is essential for the identification of

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depression because it can sift through several types of data, including text, audio, physiology, and behaviour. It identifies signs of sadness by reading between the lines of textual material and interpreting language clues and attitudes. It detects rhythmic and tonal shifts in speech that indicate emotional discomfort. Additional patterns may be revealed by physiological signs such as heart rate variability and facial emotions. Digitally analysed surveys and questionnaires provide accurate evaluations of mental health. Wearables and mobile applications improve monitoring by recording routine behaviours and interactions.

More effective treatments and better results in mental health care may be achieved by integrating machine learning with conventional approaches, which allows for the early detection and support of those struggling with depression.

By gleaning subtle patterns from complicated data, deep learning plays a crucial role in depression detection. It is able to detect mild depressive symptoms by processing a variety of inputs, including text, voice, and pictures, using neural networks. To illustrate this point, LSTMs and RNNs are quite good at text analysis because they can grasp context and pick up on subtleties in written language. Convolutional neural networks (CNNs) are used in image analysis to decipher visual indicators related to depression, such as facial expressions and body language. Methods for detecting depression are now far more accurate and effective because to deep learning's capacity to understand feature hierarchies, which allows it to discover subtle indications. There are primarily two types of algorithms used in ML and DL: supervised learning and unsupervised learning. Improving the diagnosis of individual sadness via the use of supervised learning algorithms that can understand complicated patterns and relationships within data is the primary focus of this study.

2. Literature Survey

Using a wide variety of natural language processing (NLP) techniques for data pre-processing, Musleh, D. A. used TF-IDF methods for feature extraction and N-gram ranges. It should be mentioned that our results are limited to Arabic-speaking Twitter users and may not be generalisable to other cultures or languages. Thanks to Twitter's one-of-a-kind data, we were able to record people's emotions in real time, which opens up a promising window of opportunity for the early identification of any mental health issues. Particularly, with an impressive accuracy of 82.39%, our Random Forest classifier demonstrated the model's encouraging efficacy in detecting depressive symptoms in Arabic tweets [1].

Hasib, K. M. investigated the possibility of automatically detecting depression in social network data using a variety of methods, including SVM, RF, RNN, CNN, and others. The reliability of automated depression detection systems might be compromised by potentially erroneous data sourced from social networks. When compared to more conventional approaches, these strategies provide more useful information for automated depression identification. By analysing user behaviour and mental states using social media data, a wealth of information may be uncovered [2]. Li, X. looked into the functional connection network of moderate depression and found aberrant organisation. The research may not apply to other types of depression or mental health issues since it only examines moderate depression.

Using EEG data, the procedure offers a non-invasive and objective way to diagnose moderate depression. A more thorough comprehension of anomalies in brain networks may be achieved by improving functional connectivity studies with the use of graph theory and deep learning methods (CNNs) [3].

Liu synthesised studies that used neural networks, decision trees, Support Vector Machines (SVMs), Bayes, and latent Dirichlet allocation (LDA) to identify depression symptoms in text data from social media in order to synthesise lessons from previous research. Because these studies depend so much on data collected from social media, which could not be entirely representative of the general public, it is crucial to recognise a possible weakness that has been brought to light in them: sampling bias. Regardless of this worry, ML approaches have shown promise in early symptom identification of depression, which may lead to prompt treatment and support. Public mental health professionals may benefit from a supplementary tool to better understand and manage mental health issues if ML techniques are included into mental health assessments, which might supplement existing methods [4].

According to Ashraf's research, a model was created with the express purpose of detecting sadness in Arabic users' tweets. The suggested machine learning model relies heavily on the variety and quality of the input data to function well. Utilising machine learning in this model is crucial for improving diagnostic accuracy and precision, which might lead to more dependable identification of mental discomfort like depression. Prompt mental health interventions in the digital realm are crucial, and the model's focus on early detection shows great potential in this regard, because it may help people suffering from depression get the help they need when they need it [5].

Using machine learning approaches, Amanat is building an early depression diagnosis system. Specifically, he is designing models for reliable depression prediction from text using Long Short-Term Memory (LSTM).

Recurrent Neural Networks (RNNs). Notably, the system achieves a remarkable accuracy rate of 99.0% in predicting sadness from text, even though the model may struggle to catch non-verbal signals or other forms of communication due to its dependence on textual input. This impressive result shows that Amanat's method is effective in improving the accuracy of early depression identification, since it outperforms deep learning models that are based on frequency [6].

The goal of Sajja's machine learning study is to create a tool that can anticipate depressive and anxious sensations. It is recognised that the model's performance is dependent on the variety and quality of the speech samples used for training. Sajja plans to build data-driven models that make anxiety and depression easier to research and forecast using machine learning techniques. Technology plays an important role in improving mental health evaluation and assistance, and one way to automate decision-making based on test results is to achieve more efficient and trustworthy predictions [7].

The social media remarks, posts, or messages that a person makes may be analysed by Varsha to find indications of depression. It is acknowledged that the variety and quality of the social media data used to train Varsha's algorithm affect its accuracy. As a potentially extensive and easily available source of information, the use of social media data for depression diagnosis is emphasised. Varsha uses algorithms for data mining and machine learning to improve the speed and precision of emotion detection, especially for spotting depressive symptoms. This method highlights the significance of technology in using extensive internet databases for the investigation and diagnosis of mental health issues [8].

The precise categorisation of positive and negative sentiments conveyed in tweets is the subject of Lora's study. It is recognised that the variety and quality of the Twitter dataset used for training affect the efficacy of the models generated in this work. It is emphasised that using data from Twitter is beneficial for analysing user sentiment and emotions in real-time. Notably, Lora's research makes use of a wide variety of models, including both classic ML and state-of-the-art deep learning approaches. Emotion detection in social media information may be better understood with the help of this all-encompassing method, which guarantees a complete assessment of categorisation approaches [9].

Accurately identifying positive and negative sentiments conveyed in tweets is the focus of Aleem's study. In the context of social media emotion categorisation, Aleem discusses how the quality and variety of the available data might affect the performance of machine learning algorithms for depression identification. This research demonstrates how machine learning may be used to quickly analyse large amounts of healthcare data for mental health applications, such depression identification. Researchers and practitioners in the field of mental health

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will find Aleem's work, which offers a comprehensive review of several machine learning algorithms utilised in this area, to be an invaluable resource [10].

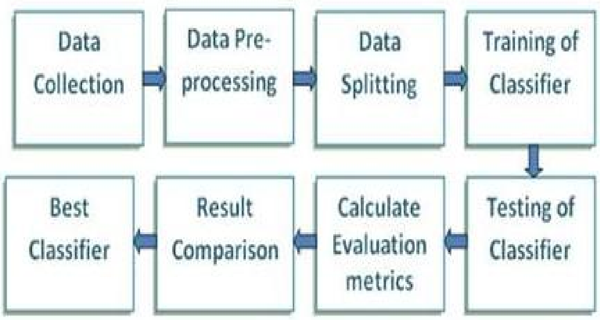
Among Flores's many accomplishments is the creation of AudiFace, a deep learning model that combines many modalities to screen for depression more effectively and efficiently. It is acknowledged that the input data's quality and variety, as well as the study's participants' characteristics, impact AudiFace's efficacy. The bulk of datasets show that AudiFace achieves the highest F1 scores for depression screening, indicating considerable improvements. One unique thing about AudiFace is how it effectively uses many modalities to improve the screening process. These modalities include audio, transcripts, and temporal facial cues. More accurate and thorough depression screening may be possible with the help of this multimodal method [11].

In his study, Khan intends to provide a comprehensive overview of Facial Emotion Recognition (FER), including methods like Random Forest (RF), Support Vector Machines (SVM), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). The review's breadth may be affected by the literature and datasets that are chosen. Regardless, combining classic ML with cutting-edge DL techniques, Khan's assessment gives a thorough introduction to FER. Notably, researchers may benefit from benchmark findings and assistance in selecting acceptable assessment measures since the study covers publicly accessible FER datasets. By taking this tack, the review becomes an even more helpful tool for those working on facial emotion recognition [12].

The goal of Kim's study is to create a system that can automatically identify cases of depression in Korean speakers by analysing their speech patterns. The study's results may not apply to other languages or cultures since they are peculiar to Korean and its cultural subtleties. However, the study by Kim presents a significant foundation for automated depression identification using voice analysis, which shows that it might be widely used, especially with cellphones. Demonstrating the usefulness of advanced methods in this setting, the research shows that deep-learned acoustic features outperform traditional approaches and pre-trained models in accurately detecting depression [13].

Islam's study entails analysing Facebook data for signs of depression in order to understand how people feel and think while interacting online. Due to the study's self-admitted dependence on Facebook as a data source, its results may not be applicable to other online platforms or social networks. However, Islam's research offers a fresh perspective on analysing data from social networks, shedding light on users' emotions and thoughts—specifically, sadness. This work provides valuable evidence that machine learning approaches can accurately diagnose depression, which opens the door to potentially scalable solutions for social media sites to treat mental health concerns. The field of using digital data to comprehend and treat online mental health issues is always developing, and our study adds to that body of knowledge [14].

Because social media sites are frequently windows into people's lives, Orabi's study takes on the complex problem of diagnosing mental illness using these sites. We recognise that the performance of the selected deep neural network designs is affected by Twitter data's unique properties, which may restrict its applicability to other social media sites. Leveraging the copious personal information accessible, Orabi's study tackles the difficulty of detecting mental illness on social media. This study uses limited text data to assess and identify the best deep neural network design for recognising symptoms of mental diseases, particularly depression [15].



3. Methodology

The generic procedures for Depression Detection are shown

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in figure 1. Here are some broad guidelines to follow while looking for signs of depression:

Data Collection:

A diverse dataset containing text data labeled with depression indicators. Include a mix of positive (indicating depression) and negative (non- depression) samples.

Fig -1: Generalised Steps for Depression Detection

Data Pre-processing:

Perform text preprocessing steps such as lowercasing, removal of stop words, and punctuation. Address imbalances in the dataset if needed (e.g., through oversampling or undersampling).

Data Splitting:

Split the dataset into training and testing sets (e.g., 80% training, 20% testing).Ensure a balanced representation of classes in both sets.

Feature Extraction:

Use techniques like TF-IDF (Term Frequency-Inverse Document Frequency) to convert text data into numerical features.

Model Training:

Choose machine learning classifiers such as Naive Bayes, SVM, or Random Forest. Train the selected classifiers on the training set using the extracted features.

Model Testing:

Apply the trained models to the testing set to predict depression labels. Generate predictions based on the learned patterns from the training data.

Model Evaluation:

It is important to evaluate the model's performance by using metrics such as accuracy, precision, recall, and the F1 score. Additionally, analyzing the confusion matrix can help to gain insight into false positives and false negatives.

Result:

Analyze the model's ability to correctly classify depression and non-depression instances. Please evaluate the balance between sensitivity and specificity in a given scenario.

Best Classifier:

Compare the performance of different classifiers.
Select the classifier with the highest overall performance based on evaluation metrics.

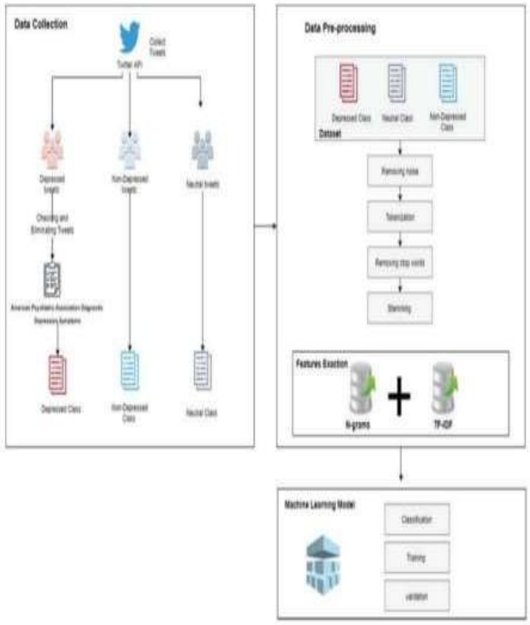

Fig. – 2: Structure of Machine Learning Models

Dataset Collection:

For this research, the CES-D survey was translated into Arabic and sent to Twitter users in that language.Twenty questions make up the brief CES-D self-reporting scale. Its purpose is to assess symptoms associated with depression. A glossary of depressed terms was also used to compile the dataset, in addition to the CES-D survey. "A delicate subject and concerning indicator of melancholy among users, the survey discovered that 45% of Arabic Tweets conveyed unhappiness or despair. Additionally, 9% of Tweets mentioned trouble sleeping, 9% said they had received too much sleep, and 8% showed thoughts of suicide.

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Data Preprocessing:

In this stage, the dataset was cleaned and prepared using natural language processing techniques, including normalization, stop word filtering, tokenization, and stemming.

Features Extraction:

Different N-gram ranges and TF-IDF methods were used to extract the required features. Six supervised machine-learning models were used to train the dataset, including SVM, RF, LR, KNN, AdaBoost, and NB.

As a result, they found the feature combination that gave optimal accuracy.

Term Frequency-Inverse Document Frequency (TF-IDF):

It is commonly used for text classification. Term frequency is the number of times a word appears within a document. Inverse document frequency is a weight term scheme that gives tokens that appear more frequently in documents a lower impact, or weight, and gives tokens that occur less frequently a higher weight.

N-gram:

N-grams extract characters or words from a text and are used in stemming spelling checking, and text compression. N-grams are a commonly used approach to identify similarities between sequences of N items, such as words or characters. The N value is an integer and is set to be a unigram n = 1 (one word or character), and a bigram n = 2 (two words).

Generating the Models

Six supervisor machine-learning models were implemented using Python. Sklearn, and Grid- Search CV libraries to determine the classification models. The classifiers were as follows:

Naive Bayes (NB)

NB is a probabilistic classifier that uses the Bayes theorem, where all features (attributes) are assumed to be independent of each other.

Support Vector Machine (SVM)

SVM is a classifier that uses risk minimization theory to find the optimal separating hyperplane within the feature space. The Simple Support Vector Machine (SVM) algorithm is commonly used for both linear regression and classification problems.

Random Forest (RF)

RF is a combination of tree predictors that predicts the class label by randomly generating a forest. The forest consists of multiple decision trees, each holding the value of an independent random vector. The trees are then equally distributed among all trees, and the final classification is based on the majority vote.

Adaboost

AdaBoost is an approach applied to textual or numeric data types. Split the data repeatedly and continue to re-assign different weights to the training data. This ensures that misclassified data from the first split will be reassigned correctly during the next data split. The process will keep going until the optimal data split is determined.

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a classification algorithm that uses the distance, such as Euclidean distance, between data points to classify new and unknown data points based on the closest existing data points.. The distance function calculates the distance between two points, and the "K" value shows the size of the neighborhood. Unknown data points are classified based on simple voting.

Logistic Regression (LR)

LR is a binary logistic model. LR is used based on one or more features to estimate the probability of binary response. The author Nadeem describes LR as a discrete choice model, as it is not technically qualified as a classification method. The relationship between the binary variables and the features is clarified through the use of the below. However, for multi-class text classifications, a multinomial extension must be used.

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Evaluation Criteria:

A comparison of all classifiers is presented and a discussion of the effect of TF-IDF on text classification. The comparison of all classifiers is based on the results of the accuracy, recall, precision, and F1-score model evaluation results. These results were obtained from the optimal parameters of the grid.

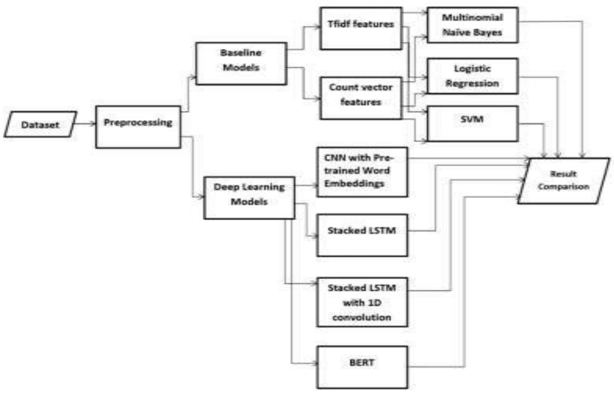

Fig. – 3: Structure of Base Line and Deep Learning Models

Dataset Collection: For the dataset, the sentiment140 dataset has been taken. The dataset contains 1048576 rows with six columns. However, only two columns have been used for this work. They are "label" (the polarity of the tweet) and "tweet" (the text of the tweet). Here zero means negative emotion tweets and 4 means positive emotion tweets.

Dataset Preprocessing

Data preprocessing is an essential phase after successfully collecting the dataset. In the real world, there can be some unnecessary, missing, and noisy data for their huge size. By preprocessing, it is possible to remove this unnecessary data to reduce the size of huge data. Besides, preprocessing can reduce computation complexity. So, it needs to be preprocessed to remove noisy data and reduce complexity.

Data preprocessing which has been done involved the following steps:

- Converting uppercase letters to lowercase
- Removing punctuations
- Removing hashtags, URLs, retweet mentions and user mentions
- Replacing multiple spaces with one space

Baseline Models:

Three baseline models were developed for this study using both Tf-idf and count vectors. Tweets were transformed into feature matrices using the Tfidf Vectorizer with specific parameters. For count vectors, Count Vectorizer was employed. The models include Multinomial Naive Bayes, Linear SVM, and Logistic Regression, utilizing respective sci-kit-learn libraries. The data was split with 90% for training and 10% for testing.

Deep Learning Models:

Convolutional Neural Network (CNN) with Pre-trained Word Embeddings: Based on the pre-trained word embeddings from the Google News Word2Vec model, this book explains how to create a Convolutional Neural Network (CNN) for binary text categorisation. The CNN starts with five distinct filter sizes, then moves on to GlobalMaxPooling1D layers, and finally uses relu activation in a succession of Dense and Dropout layers. Accuracy on both the training and validation sets increases throughout training, which is a favourable sign of high performance.

Sno	Method	Dataset	Accuracy	Precision	Recall	F1-Score
1	RF	CES-D survey	83%	82.40%	82.67%	82.52%
2	SVM	DAIC-WoZ	80%	77%	87%	-
3	CNN	BDI-II	80.1%	-	-	-
4	LSTM	WOZ-DAIC	93%	-	-	87%
5	SVM	DAIC	64%	80.25%	-	69.52%
6	RNN	data set of tweets from the Kaggle website	99%	99%	98%	99%
7	SVM	600 records in the input data set	94%	-	-	-
8	SVM	collected almost 10,000 data from Facebook	75%	77%	80%	78%
9	CNN	sentiment140	84%	83%	84%	83%
10	SVM	PHQ-9	95%	95%	-	97%
11	Audi Face	DAIC-WOZ	-	-	-	93%
12	CNN	Cohen Knede	-	-	-	-
13	CNN	153 patients, 165 healthy data	78.14%	76.86%	77.90%	77.27%
14	LIWC	Facebook users' comments	80%	-	-	-
15	CNN	1,145 Twitter users	87.95%	87.43%	87.02%	86.96%

One possible area for improvement is the validation loss, which is somewhat more than the training loss. The model underwent training using Adam optimisation across three epochs, a dropout probability of 0.1, and a batch size of 34. Seventy percent of the dataset was reserved for training, ten percent for validation, and twenty percent for testing.

Stacked LSTM Model: A Stacked LSTM model, an expansion of the initial LSTM, is presented in this article. It consists of several hidden layers that house numerous memory cells. Possible overfitting is indicated by the training process's erratic accuracy on the validation and training sets. The model was trained using Tanh activation, Adam optimisation across three epochs, and a dropout probability of 0.2. There was a 70% training set, 10% validation set, and 20% testing set inside the dataset. Epoch 2 sees a decline in validation accuracy, which may indicate a loss of predictive power when dealing with fresh data. Furthermore, overfitting may be occurring because validation loss is greater than training loss.

Stacked LSTM with 1D Convolution: An additional 1D convolutional layer was added to the previous model to speed up training. This model used a dropout probability of 0.3, a kernel size of 5, a pool size of 4, and madam optimization, and was trained for 3 epochs with Tanh activation. The training process shows increasing accuracy on both training and validation sets, indicating good performance.

Training loss is slightly higher than validation loss, suggesting potential for further improvement. This model outperforms the previous one.

BERT-Based Model: BERT (Bidirectional Encoder Representations from Transformers) is a model pre-trained on English Wikipedia and Brown Corpus by Google. It enhances computer understanding of language for tasks like complex search queries. Implemented with TensorFlow 2.0, we used a batch size of 32, a drop-out rate of 0.2, and trained for 5 epochs. The model achieved an accuracy of 83.2%.

Evaluation Parameters:

Results of Baseline Models and Deep Learning Models Parameters such as accuracy, precision, recall, specificity, and the F1-score were used.

4. Results

The findings of fifteen separate scholarly articles are combined in the table above. Included are the articles' respective methodologies and performance measures.

5. Conclusion

To sum up, studying cough sounds for signs of depression using a combination of classical approaches like support vector machines (SVMs), linear regression (LRs), and random forests (RF) and machine learning algorithms like convolutional neural networks (CNNs) and long short-term memory (LSTMs) offers a potential route. People in low-income brackets or living in places with inadequate medical infrastructure may find diagnostic tools more accessible via the creation of mobile apps that use these frameworks.The aforementioned models have accuracy rates higher than 90%, however before using these technologies in clinical settings, it is crucial to stress the need of complete validation, regulatory clearance, and ethical concerns. Because depression is a complicated mental illness, it is essential that any diagnostic method used to identify it be accurate, precise, and trustworthy. Furthermore, it is essential that healthcare experts be involved in analysing and verifying the data.Technology has the ability to greatly expand access to mental health diagnoses, which might lead to earlier intervention and better support for those struggling with depression. To guarantee these tools are safe, effective, and contribute to the overall well-being of people afflicted by depression, responsible development, validation, and ethical application are of the utmost importance.

Anticipating the future, academics, physicians, and engineers may work together to enhance and broaden the capabilities of technologies that identify depression. It will be crucial to continuously validate machine learning models and develop them using bigger and more varied datasets. Furthermore, in order to responsibly incorporate new technologies into mental health treatment, it is essential to create standardised norms for ethical deployment and ensure compliance with regulatory frameworks.

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