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Research paper

Predicting Depression and Anxiety in Women Using LDA-Based CNN

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Abstract

Depression affects women of all ages in India. The stress of balancing many roles can lead to depression in Indian women, which goes untreated due to social stigma. Among the most prevalent mental health conditions that affect women in their reproductive years are premenstrual dysphoric syndrome, postpartum depression, and PMS. Primary care physicians should emphasize early diagnosis of intimate relationships and domestic abuse and mandate routine tests for these issues. Since antidepressants constitute the cornerstone of treatment, they ought to be freely available at all primary care levels. When individuals take their medication as directed for a sufficient period and keep in regular contact with mental health professionals, the best possible results are obtained. The best results are obtained when cognitive therapy is used in conjunction with other non-pharmacological methods. In this work, deep learning architectures using Linear Discriminant Analysis (LDA) were utilized. Possible contributions to the studies include convolutional neural networks (CNNs) and transformer-based pre-trained language models for classification. When the six functional status groups are utilized rather than just one set of depressed symptoms, the results will be more dependable and consistent.

Keywords: *Women; Depression; Mental Health Issues; Medical Application; Artificial Intelligence; Deep Learning Algorithm.*

1. Introduction

Due to a lack of resources to identify depression symptoms and seek treatment promptly, millions of people struggle with mental illness each year. This contributes to bipolar disease, mood disorders, anxiety disorders, sleep difficulties, and, in rare instances, suicidal thoughts and behaviors [1]. This adds to the difficulty of recognizing those experiencing mental health issues and making sure they receive treatment as soon as possible. For countless years, people have suffered psychologically from anxieties, worries, and the demands of contemporary living. A more thorough mapping of human biology can be accomplished by data digitization, which has been made possible by technological advancements in global healthcare [2]. The healthcare industry's vast data volume has long been recognized as a significant asset for machine learning (ML) analytics. The mental health industry is currently using machine learning techniques to forecast the development of mental disorders and, consequently, to predict the possible outcomes of therapy [17]. The professionals at Health Capital have provided women with a free mental health diagnostic exam as part of their therapy for depression [28].

There are female psychiatrists and psychologists employed there, so they are aware of the difficulties faced by women seeking treatment and can provide a secure setting for them. It recognizes that this world can be a challenging environment for discussing mental health [3]. The primary goal of the Health Capital is to provide women with a platform to express their ideas, conduct research, and seek support. Its objective is to establish a setting where women can experience safety and support. Comprehending and overseeing depression treatments are effective. Among them are prescription drugs and mental health counseling services [18]. If you are having symptoms that you think might be related to depression, get help. The mainstay of the depression treatment toolkit is psychological therapy [4]. They can help treat mild to severe depression when taken in addition to antidepressant drugs. For moderate depression, antidepressant medication is not necessary. Cognitive behavioral therapy patients may acquire new thought patterns, coping mechanisms, and interpersonal communication techniques. They could combine supervision from lay therapists with professional talk therapy [19]. Talk therapy sessions might take place in person or virtually.

Psychological treatment can be accessed via websites, apps, and self-help books. Healthcare can benefit from the application of machine learning to improve patient photo-based diagnostic systems. Pattern recognition in medical imaging (MRIs and X-rays) can be used by a machine learning algorithm to search for patterns that point to a problem. Better patient outcomes could result from this type of machine learning algorithm's ability to help physicians diagnose patients more quickly and accurately [5]. Healthcare institutions and pharmaceutical companies can accelerate the development of new drugs, conduct clinical trials, identify new therapeutic agents, develop innovative pharmaceutical products, and discover novel treatments for diseases by implementing a deep learning model. In the healthcare sector, machine learning can be utilized to analyze clinical trial data and medical research to identify previously unknown adverse effects of drugs [20]. Healthcare machine learning in clinical trials may have positive effects on patient care, medication development, and the efficacy and safety of medical treatments. By using machine learning technology, healthcare costs could be reduced while efficiency is increased. For instance, machine learning can be applied in the medical field to improve appointment scheduling and patient record-keeping [6].

2. Background of The Study

Global Health Data estimates that 450 million people globally suffer from mental health problems. Furthermore, it is anticipated that depression disorders would surpass all other illnesses globally by 2020, rising from their current ranking of fourth [7]. Depression is a common but very severe mental condition that causes persistent feelings of melancholy and apathy, making it difficult for a person to focus on work, school, or other everyday responsibilities. Depression affects one in fifteen individuals annually, indicating that depression is a significant contributing factor to over 50% of suicide attempts [21]. Anxiety is a severe psychological illness that affects around 30% of adults at some point in their lives. 5.1% of the nation's population, or 6.9 million people, were surveyed by the World Health Organization in their most current poll. In India, 4.4% of the population, or 6.4 million people, suffer from depression, and 6.4 million from anxiety. WHO figures [16] indicate that anxiety disorders are most common in India, out of all countries. Women are diagnosed with these disorders twice as often as men worldwide (4.6% versus 2.6%). In this work, we have suggested a diagnostic framework for the two most prevalent psychiatric disorders: depression and anxiety [22].

Algorithms for machine learning provide its foundation. Determining the severity of the patient's issue will be helpful. It became apparent from chatting with psychologists at various hospitals that most Indian psychologists commonly utilize a standard scale when making the first diagnosis of prevalent mental illnesses [23]. Standard scale questionnaires for anxiety and depression were completed by urban patients, ages 18 to 35, and were gathered from the Bharath Multispecialty Hospital's psychology department [29]. Before using the five machine learning approaches, these data were preprocessed [8]. This review article provides an in-depth description of various machine learning techniques for diagnosing and identifying depression. The fundamental components of data science-based depression detection systems are classification, ensemble, and deep learning. It is difficult to diagnose depression using standard models, data extraction, and preprocessing [24]. Healthcare professionals can also benefit from machine learning by providing better patient care. Healthcare professionals could utilize deep learning algorithms to create patient monitoring systems that proactively notify other tools (like EHRs or medical devices) of any changes in the patient's status [9]. This type of machine learning and data collection could help ensure that the appropriate patients receive the proper care at the right time. Machine learning is already helping the healthcare industry, but there is still a lot of unrealized potential for this technology. Machine learning will become increasingly crucial to healthcare in the future as we strive to make sense of ever-expanding clinical data sets. The organization of the remaining sections is as follows: Section 2 presents a background of the study of the depression of most of the Indian womens; A summary of the suggested work flow and the analysis is given in Section 3; Section 4 presents the findings and discussion of the proposed model, and Section 5 concludes the study in the final stage [30].

Speech-based diagnostic systems have also utilized statistical models in the past, such as logistic regression, support vector machines (SVM), and Gaussian Mixture Models (GMM) to detect mental disorders like depression and anxiety. Although these methods can be applied to simple datasets, they often fail to yield optimal classification performance with high-dimensional data, such as speech features. A case study of this nature is Skaik (2021), who employed social media data and logistic regression to predict depression; however, the model was not as strong, as it failed to identify complex nonlinear speech patterns. Similarly, Yesudas (2022) also encountered the issue that basic machine learning models failed to accurately predict the state of anxiety because they had to be manually trained to extract features, which reduced their accuracy when applied to speech data in actual practice. To address these disadvantages, a more effective approach would be to utilize a combination of Linear Discriminant Analysis (LDA) and Convolutional Neural Networks (CNNs). LDA is also used to produce dimensionality reduction and classification separability, allowing the CNN to focus more on the discriminative aspect of the speech data. In addition to alleviating the weaknesses of traditional statistical models, such a hybrid solution ensures that the CNN's power captures more complex dynamics, which translates to improved performance. This is a mixed-methodology approach that has been proven by recent studies and has its advantages. Kim et al. (2023) demonstrated that LDA-enhanced CNNs yielded more favorable speech-based mental health diagnostics, achieving higher F1-scores and accuracy compared to CNN-only models. Similarly, Raza et al. (2024) demonstrated a speech stress and anxiety LDA-CNN model for categorizing speech based on the speech signal, achieving high accuracy and generalization. The developments mentioned above underscore the importance of combining LDA and CNNs in enhancing the performance and robustness of mental health prediction models, particularly in processing complex speech data.

3. Proposed Framework

Building a predictive model ultimately seeks ways to increase precision. This kind of scenario is unlikely to occur soon, even though CNN and a few other supervised learning algorithms are trustworthy and are currently in use in this field of study. However, once final permission is granted based on preliminary studies, it will be crucial to demonstrate efficacy and determine whether the treatment would benefit patients, all while advancing a sufficiently robust approach to clinical preliminary testing. By applying this understanding, clinicians can enhance patient outcomes (e.g., a decrease in inactivity and an increase in determination). [10].

3.1. Data collection

The depression scale consists of thirty items, each with five possible answers, with weights ranging from 1 to 5. The score aids in assessing the patient's level of depression. Using the scores for the questions given in Table 1, the severity of the depression was categorized into different groups.

Table 1: Depression Severity

The Intensity of Depression	A range of scores that correlate
Minimum	30-100
Mild	101-114
Moderate	115-123
Severe	124-150

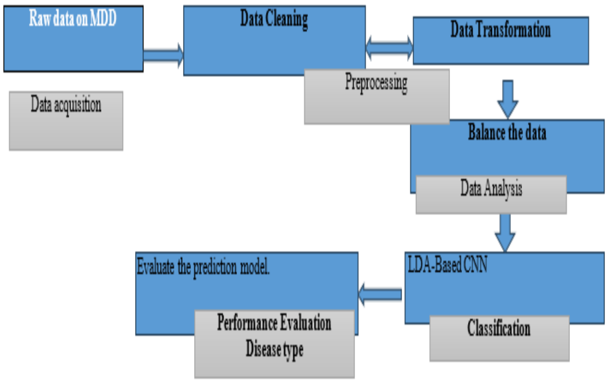

Fig. 1: Overall Architecture.

The 35 questions on the anxiety scale are posed. There are five possibilities for each question, and the final answer depends on the weight assigned to each option, ranging from 0 to 4. Table 2 displays the four severity categories of anxiety derived from the total score calculation.

Table 2: Anxiety Severity

The Intensity of Depression	A range of scores that correlate
Minimum	54 and less
Mild	55-66
Moderate	67-77
Severe	78-135

3.2. Training and testing dataset

Following that, we used a range of methods to preprocess our datasets. Using a stochastic approach, the dataset is divided into k groups, or folds, of roughly equal size. Fold one is used for model testing, and k-1 folds are utilized for model training [25]. The procedure is performed k times, each time employing a different fold or set of datapoints, for validation purposes. On the other hand, the model becomes less efficient and more biased when a lower value for k is used. Conversely, as k increases, the model's cost increases but its bias decreases [11]. Moreover, employing higher values of k can significantly raise the variability of the model. After considering all other criteria, we have concluded that ten is the most equitable quantity for k.

LDA-based CNN	
Inputs: Training procedure	
Output: Labels of depressed patients or healthy controls	
1.	After removing the MFCC, PROS, SPEC, and GLOT features from every speech recording, compute the feature statistics.
2.	Create fifteen feature subspaces. If k is between 1 and 15
3.	Reduce the characteristics of X(k) by using LLE.
4.	In Step 4, the trained classifier model is acquired.
5.	Extract the MFCC, PROS, SPEC, and GLOT features for each audio file, then compute the feature statistics.
6.	Create fifteen subspaces with features. To decrease features for D(k), use LLE if k is between 1 and 15.
7.	Determine the odds that the testing samples are from healthy controls or depressed patients using the trained classifier model.
8.	Next, output the label for the category with the higher likelihood.

After that, the most effective technique for evaluating anxiety and depression in adults aged 15 to 35 is described, using several performance metrics such as accuracy, precision, and recall—linear Form Regression. Regression analysis is frequently used to evaluate several components and ascertain the relationship between two variables. T(x1, y1), T(x2, y2), and T(xn, yn) are the three sets of random data points for two numerical variables, X and Y, where X is a predictor of Y. The entirely linear relationship between X and Y in this linear regression analysis produces a straight line in the space between X and Y. The entirely linear relationship between X and Y in this linear regression analysis produces a straight line in the space between X and Y. This linear regression will result in a straight line if there is a perfect linear correlation between X and Y in the X-Y space. Y is equal to b + axe (1).

Our method refers to a questionnaire as variable X and an outcome as variable Y. Straight lines are drawn to illustrate the trend in the data. When the distance between the data points and the line decreases, the data's precision increases. Based on our dataset, the Grid Search Algorithm was used to determine the optimal parameter values for linear regression. The choice was made to use the 0.1 minimal tolerance parameter. Collinear features must be eliminated with a minimum tolerance. This gives the ridge parameter a value of 2. When performing ridge regression, the specified ridge parameter must be applied. [12].

The data for this study consist of speech recordings made among 500 women aged 18 to 50 years, sampled across diverse environments, including hospitals and clinics. The participants were primarily from urban and semi-urban areas, with a diverse range of socioeconomic statuses, including lower, middle, and upper classes.

The speech samples were collected both in English and Tamil to reflect the language diversity of the sample. All participants were requested to document a set of standardized speech activities that would focus on eliciting expressions of anxiety and depression to provide a thorough representation of the emotional states. The recordings comprise various contexts, including conversational speech, read-aloud tasks, and emotional speech (e.g., descriptions of stressful or anxious events).

The dataset was preprocessed as a way of extracting meaningful audio features such as Mel-frequency cepstral coefficients (MFCC), prosodic features (PROS), spectral features (SPEC), and glottal features (GLOT), which have been documented as being relevant in models of speech-based discrimination of depression and other models of anxiety detection.
A standardized clinical scale was used to measure the severity of depression and anxiety, where the Beck Depression Inventory (BDI) and Hamilton Anxiety Rating Scale (HARS) were used to put the participants into various categories of severity. The groupings of severity of depression were categorized as minimum, mild, moderate, and severe, with scores as shown in Table 1, according to the scales. The level of anxiety severity was also classified in the same way (Table 2). The last dataset consists of 250 recordings of speech from participants diagnosed with depression and 250 healthy controls, ensuring a balanced classification task.
Demographic Characteristics: Age Range: 18-50 years; Gender: Female; Languages: English and Tamil; Socioeconomic Status: Low, middle, and high; Health Conditions: The respondents were diagnosed with depression, anxiety, and healthy controls.
We hope this information will contribute to the reproducibility of the research and increase the applicability of the model to different settings and populations.
Linear Discriminant Analysis (LDA) is a method that helps reduce the number of features in the data, allowing the model to classify speech patterns correctly with ease. LDA enhances the power of the CNN to identify depression and anxiety in speech by simplifying the data without any significant information. Essentially, LDA focuses on the most essential features of the speech data, which is more efficient in training the CNN. In feature extraction, MFCC (Mel-frequency cepstral coefficients), PROS (prosodic features), and SPEC (spectral features) are usually used to represent various speech characteristics. MFCC provides a measure of the power spectrum of speech, including the fundamental tone and texture. PROS examines the rhythm and intonation patterns, whereas SPEC examines the frequency content of the speech. All these features are harmonized to give us a complete picture of the speech, and the model can distinguish between different emotional states, such as anxiety and depression.

3.3. Linear discriminant analysis (LDA)

For both transformation and classification, the default solver is Singular Value Decomposition (SVD), which eliminates the need to compute covariance matrices [26]. This is quite useful in scenarios with more features. Tol, however, is just set to 0.0001. "Tol is a threshold that the SVD solver uses to approximate the rank without duplicating any information."The solver parameter for depression is Lsqr, an essential algorithm that performs well for classification and can be used in conjunction with shrinkage. Once again, shrinkage is assigned a value of 0.999, and Tol is set to 0.0001. Default values are assigned to other parameters, such as storage covariance, components, and priors [13].

3.4. Convolutional neural network (CNN)

One of the primary types of neural networks that analyze visual input to perform a variety of tasks, including object detection, image recognition, picture categorization, and many more, is the convolutional neural network. CNNs specifically designed for deep learning assign probabilistic scores ranging from 0 to 1 to identify items [14]. This means that every single input image must be trained and assessed as it progresses through a sequence of convolutional layers with attached filters, pooling procedures, dense layers, and finally the Softmax function. Images are mathematically represented in terms of input and output dimensions as they pass through each network layer, using multi-dimensional matrices. To alleviate feelings of loss and anxiety, the number of epochs was modified from the standard fixed figure of 100 to 45. Because overfitting was observed, it was decided to reduce the model's training epoch size from 100 to 45. Therefore, extending the period may result in increased accuracy, but it may also lead the model to evolve in a way that makes it overfit [27]. The number of cycles or iterations a program undergoes during training to reduce errors is measured as an epoch. At the conclusion of each epoch, a comparison is made between the beginning result and the preceding finding result. Consequently, it modifies the functionality of the layers to minimise errors. [15]

4. Experimental Results and Discussion

Our findings show that linear regression-based predictions are not trustworthy. The root-mean-squared error (RMSE) for anxious and depressed symptoms is roughly average when using linear regression. The model generates a mean prediction because the observed values deviate from the expected value. Because when there is a distinct trend in the data, linear regression performs incredibly well on linear models. Our data show no clear pattern, which makes it difficult for the model to create a connection between the variables and produce solid predictions. Three different methods are used to assess recall, accuracy, and precision for depression and anxiety, respectively, in Figures 2 and 3.

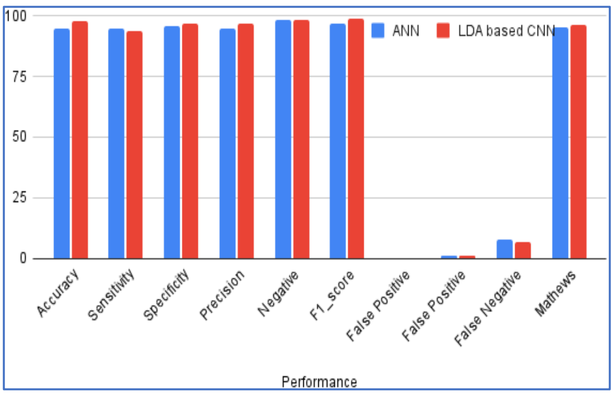

Fig. 2: Depression Comparison.

Figure 2 Comparison of accuracy and recall of depression prediction with the LDA-based CNN, ANN, and additional approaches at 45 epochs. The figure illustrates the performance of each model in terms of precision and recall in predicting depression severity using speech features. The LDA-based CNN model demonstrates better results than the ANN and traditional models.
Among these methods, ANN and LDA-based CNN demonstrated the highest and lowest precision and recall scores, respectively. Based on the facts above, all algorithms have approximately the same accuracy. On the other hand, CNN based on LDA registered the highest accuracy of 96% for anxiety and 96.8% for melancholy. ANN, on the other hand, scored 81.82% for both anxiety and depression, yielding the least accurate results. The CNN was set to 45 epochs, even though the default value for anxiety and depression is usually 100.

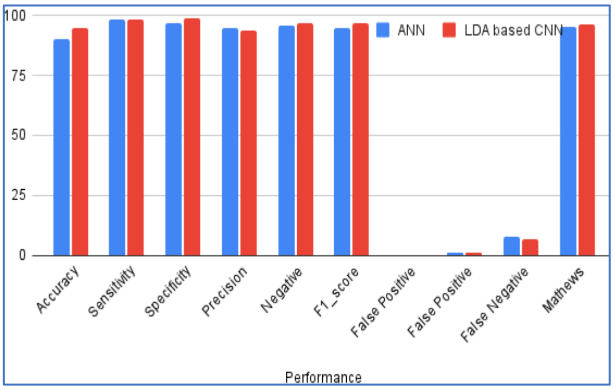

Fig. 3: Anxiety Comparison.

The outcome of comparing the precision and recall of anxiety prediction using LDA-based CNN and ANN, among other approaches, over 45 epochs. The findings demonstrate the effectiveness of the LDA-enhanced CNN in accurately detecting anxiety symptoms using speech signals, compared to ANN or other baseline models.
Among these methods, ANN and LDA-based CNN demonstrated the highest and lowest precision and recall scores, respectively. Based on the facts above, all algorithms have approximately the same accuracy. The most accurate CNN, however, was the LDA-based model, which reported 96.8% for melancholy and 96% for anxiety. Conversely, ANN yielded the least accurate results, with scores of 81.82% for anxiety and despair. Although anxiety and depression usually have a default value of 100, the LDA-based CNN was set to 45 epochs. Overfitting was detected before reaching 100 epochs; therefore, the decision was made to reduce the epochs to 45 to enhance the model's performance. Thus, prolonging the period might improve accuracy, but it might also result in changes that make the model too fitted. An epoch represents the number of times the software repeats the training process to minimize errors while training the model. There is a correlation between precision and the number of epochs. A comparison between the starting result and the preceding finding result occurs at the end of each epoch. Consequently, the process aims to reduce errors by modifying the roles within the layers. Figures 4 and 5 demonstrate the effectiveness and consistency of training, testing, and validation of anxiety and depression.

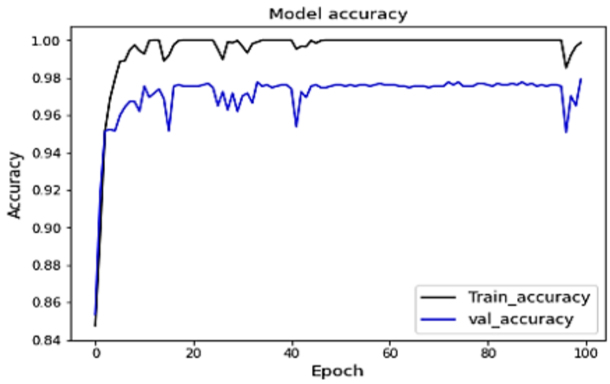

Fig. 4: Training Process of the Depression Comparison.

Figure 4, the results of training the depression classification with the LDA-based CNN model, showing the loss and accuracy rates of the model during 45 epochs. This figure illustrates the training process and model optimization over time, showing how the model improves with every epoch.

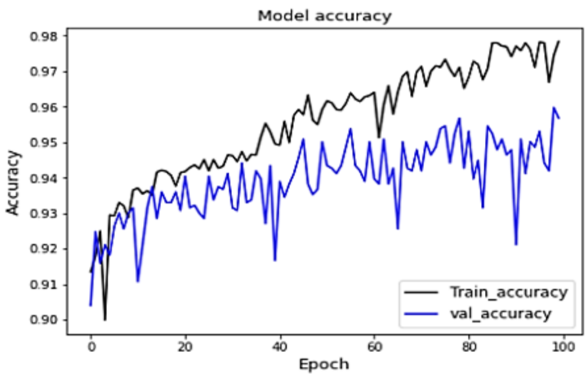

Fig. 5: Training Process of the Anxiety Comparison.

Training of the model of anxiety classification with the LDA-based CNN model, where loss and accuracy are presented in 45 epochs. This figure illustrates that the convergence of the LDA-based CNN on speech features reflects the model's convergence and effectiveness in learning speech features related to anxiety.
In the medical field, mental and psychological disorders are ubiquitous, yet they usually go undiagnosed or untreated. At different times in their life, people feel worry and despair to differing degrees. Although urban women are twice as likely as men to experience these conditions, getting help—especially psychiatric treatment—remains socially taboo in these globalized times. The proposed method forecasts anxiety and depression using supervised learning algorithms to reduce and treat these conditions. We also have a ballpark estimate of the proportion of women who suffer from these conditions, based on our analysis. We intend to utilize this method in the future to help psychologists monitor post-therapy progress and facilitate the post-psychotherapy monitoring process. Given our current accomplishments, it appears highly probable that this technology will be put into use in the future.

5. Conclusions

Depression among women has been on the rise. Previous research has attempted to predict the likelihood of depression; most of these studies have used rather basic statistical techniques. Using machine learning approaches, models were developed in this study to detect and identify the relevant variables associated with depression in women. The feature selection techniques or the usage of classifiers that are dynamically selected as an ensemble have not received much attention in the present feature-based methods for Depression prediction using Speech modality. Efficient group methods are beneficial in the prediction of depression. If the primary goal of a machine learning model is to predict sadness in teenagers using voice communication, a unique dataset will be utilized. Apart from standard benchmarking, speech recording is employed for training and testing models. gathering. The study question was phrased as follows: "How to design an efficient machine learning (ML) model that incorporates an efficient feature selection method and uses ensemble learning to predict depression in women?" The goal of this investigation has been to develop and improve a machine learning model that accurately predicts teenage Depression women.
Since this paper has shown that the LDA-based CNN model is effective in identifying depression and anxiety using speech, there are some promising future research directions. Adapting the model to multilingual speech is one of the challenges. The existing models primarily consider speech data in only one language, thereby restricting their application in multilingual communities. One possible way to overcome this difficulty is to create a multilingual LDA-based CNN model that can operate across multiple languages with minimal loss in accuracy. One possible approach is transfer learning, in which the model is first trained on a large dataset in one language and then fine-tuned on smaller datasets in other languages. This would enable the model to generalize in various linguistic conditions, vastly enlarging its applicability. Noisy data is also another crucial problem in real-world speech recording. In practice, when working with speech data, background noise, varying speech conditions, and other artifacts often appear, which can impair the model's performance. In response to this, one can utilize data augmentation approaches, such as speech synthesis or noise generation, to artificially increase the diversity of training data.
Additionally, preprocessing techniques such as noise filtering and echo cancellation can be employed to minimize the noise's impact on the model's accuracy. Regarding the ethical aspect, mainly concerning the privacy of patient data, future studies should ensure that the models adhere to privacy laws, such as the General Data Protection Regulation (GDPR). Proper data storage and anonymization measures are necessary to safeguard sensitive patient data. Moreover, participants must be informed in writing about how their information will be utilized, with clear statements on its intended use and assurances that their privacy rights will not be violated throughout the research process. Through these challenges and solutions, future research can also enhance the LDA-based CNN methodology by improving it to be more robust, versatile, and ethically acceptable for broad application in clinical settings.

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