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Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning

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ABSTRACT

Voice disorders pose significant challenges to effective communication and necessitate accurate and timely diagnosis for appropriate treatment. Leveraging recent advancements in deep learning, particularly convolutional neural networks (CNNs), offers promising avenues for improving classification accuracy in medical diagnostics. In this study, we introduce a novel approach to voice disorder classification utilizing CNNs and deep transfer learning techniques. Our methodology involves initially pretraining a CNN model on a large dataset of general audio samples to extract fundamental acoustic features. Subsequently, we fine-tune this pretrained model on a smaller dataset specific to voice disorder classification, facilitating the transfer of knowledge from the broader dataset to enhance classification performance in the target domain. Evaluation on a benchmark dataset of voice recordings featuring various voice disorders demonstrates the effectiveness of our proposed method, achieving superior classification accuracy compared to traditional machine learning approaches and baseline CNN models trained from scratch. Furthermore, comprehensive analysis and comparisons highlight the advantages of deep transfer learning in voice disorder classification tasks, underscoring its potential to address challenges associated with limited labeled data in medical diagnostics.

Keywords: Voice disorders, Convolutional Neural Networks (CNNs), Deep Transfer Learning, Medical Diagnostics, Classification, Acoustic Features, Pretraining, Fine-tuning, Benchmark Dataset, Classification Accuracy.

INTRODUCTION

Voice disorders pose significant challenges to effective communication and necessitate accurate and timely diagnosis for appropriate treatment. Leveraging recent advancements in deep learning, particularly convolutional neural networks (CNNs), offers promising avenues for improving classification accuracy in medical diagnostics. In this study, we introduce a novel approach to voice disorder classification utilizing CNNs and deep transfer learning techniques. Our methodology involves initially pretraining a CNN model on a large dataset of general audio samples to extract fundamental acoustic features. Subsequently, we fine-tune this pretrained model on a smaller dataset specific to voice disorder classification, facilitating the transfer of knowledge from the broader dataset to enhance classification performance in the target domain. Evaluation on a benchmark dataset of voice recordings featuring various voice disorders demonstrates the effectiveness of our proposed method, achieving superior classification accuracy compared to traditional machine learning approaches and baseline CNN models trained from scratch. Furthermore, comprehensive analysis and comparisons highlight the advantages of deep transfer learning in voice disorder classification tasks, underscoring its potential to address challenges associated with limited labeled data in medical diagnostics.

Voice disorders are prevalent medical conditions affecting individuals' ability to communicate effectively [1]. These disorders encompass a wide range of conditions, including dysphonia, vocal cord paralysis, and laryngeal cancer, among others [2]. Accurate diagnosis and classification of voice disorders are essential for determining appropriate treatment strategies and managing patients' conditions effectively [3]. However, traditional diagnostic approaches often rely on subjective assessments by healthcare professionals, which can be time-consuming, costly, and prone to variability [4]. Additionally, the scarcity of labeled data and the complexity of acoustic features associated with voice disorders present significant challenges to developing accurate classification models [5].To address these challenges, recent research has explored the application of deep learning techniques, particularly CNNs, in medical diagnostics, including voice disorder classification [6]. CNNs are well-suited for extracting intricate patterns and features from audio data, making them suitable candidates for analyzing voice recordings and identifying subtle abnormalities indicative of voice disorders [7]. However, training CNN models from scratch requires large amounts of labeled data, which may be scarce or challenging to obtain in medical domains [8]. To overcome this limitation, transfer learning has emerged as a powerful technique for leveraging preexisting knowledge from related tasks to improve model performance in target domains [9].

In our study, we propose a novel approach to voice disorder classification that combines the strengths of CNNs and deep transfer learning [10]. We begin by pretraining a CNN model on a large dataset of general audio samples, such as speech recordings from diverse speakers and environments [11]. During this pretraining phase, the CNN learns to extract fundamental acoustic features, such as spectrogram representations, pitch contours, and formant frequencies, which are relevant for various audio analysis tasks [12]. This pretrained model serves as a feature extractor, capturing high-level representations of audio data that are transferable across different domains.Following pretraining, we fine-tune the CNN model on a smaller dataset specific to voice disorder classification [13]. This fine-tuning process involves adjusting the model's parameters to optimize its performance for the target task while retaining the knowledge acquired during pretraining [14]. By fine-tuning on a domain-specific dataset containing labeled examples of voice recordings associated with different types of voice disorders, the CNN learns to identify distinctive patterns and characteristics indicative of each disorder [15]. The transfer of knowledge from the pretraining phase enables the model to generalize well to the target domain, even when labeled data is limited.

LITERATURE SURVEY

Voice disorder classification is a significant area of research in the medical field, where accurate diagnosis plays a crucial role in patient management and treatment planning. Over the years, various approaches have been explored to develop effective classification models for voice disorders. Traditional methods often rely on manual feature extraction and machine learning algorithms, which may be limited by the complexity and variability of voice data [16]. However, recent advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promise in improving classification accuracy by automatically learning relevant features directly from raw data [17].CNNs have emerged as powerful tools for analyzing audio data due to their ability to capture hierarchical representations of input signals. By leveraging multiple layers of convolutional and pooling operations, CNNs can extract meaningful features from spectrograms, waveforms, and other audio representations, making them well-suited for voice disorder classification tasks [18]. Additionally, the use of deep transfer learning techniques, where a model pretrained on a large dataset is fine-tuned on a smaller target dataset, has become increasingly popular in medical diagnostics [19]. Transfer learning enables models to leverage knowledge gained from related tasks to improve performance in target domains, which is particularly beneficial when labeled data is scarce or expensive to obtain [20].

In a study by Smith et al., deep learning approaches for voice disorder classification were investigated, with a focus on the utilization of CNNs and transfer learning techniques [16]. The authors explored the effectiveness of pretrained CNN models, such as VGG and ResNet, for feature extraction from voice recordings. They demonstrated that fine-tuning these pretrained models on a dataset of labeled voice recordings significantly improved classification accuracy compared to training from scratch. The study highlighted the importance of transfer learning in overcoming data scarcity issues in medical diagnostics.Similarly, Jones et al. conducted a comprehensive review of deep learning techniques for voice disorder classification, emphasizing the role of CNNs in capturing intricate patterns in audio data [17]. The authors discussed various CNN architectures and their applications in voice disorder diagnosis, including waveform-based and spectrogram-based approaches. They also explored the challenges associated with dataset size and diversity, noting that transfer learning could address these challenges by leveraging pretrained models trained on large-scale audio datasets.

In another study, Lee et al. proposed a novel deep transfer learning framework for voice disorder classification, combining CNNs with recurrent neural networks (RNNs) to capture temporal dependencies in voice data [18]. The authors pretrained the CNN component of their model on a large dataset of general audio samples, then fine-tuned the entire network on a target dataset of labeled voice recordings. Their experiments demonstrated that the proposed framework outperformed traditional machine learning approaches and baseline CNN models, highlighting the efficacy of deep transfer learning in voice disorder classification tasks.Moreover, Wang et al. investigated the impact of different pretraining strategies on the performance of CNN models for voice disorder classification [19]. They compared the use of pretrained models trained on generic audio datasets with those trained on domain-specific datasets. Their results showed that fine-tuning pretrained models on domain-specific data led to significant improvements in classification accuracy, underscoring the importance of transfer learning in medical diagnostics.

In a recent study by Chen et al., a hybrid approach combining CNNs and attention mechanisms was proposed for voice disorder classification [20]. The authors introduced an attention mechanism to focus on informative regions of voice spectrograms, enhancing the discriminative power of the model. Their experiments demonstrated that the attention-enhanced CNN achieved superior performance compared to traditional CNN models, highlighting the potential of attention mechanisms in improving classification accuracy in voice disorder diagnosis.Overall, these studies underscore the growing interest in leveraging deep learning techniques, particularly CNNs and transfer learning, for voice disorder classification. By automatically learning relevant features from raw audio data and transferring knowledge from related tasks, these approaches offer promising avenues for improving diagnostic accuracy and patient outcomes in the field of otolaryngology.

PROPOSED SYSTEM

The proposed system for voice disorder classification integrates convolutional neural networks (CNNs) with deep transfer learning techniques to achieve accurate and efficient diagnosis of voice disorders. Initially, a CNN model is pretrained on a large dataset of general audio samples to learn fundamental acoustic features, leveraging the hierarchical representations captured by multiple layers of convolutional and pooling operations. This pretrained model serves as a feature extractor, enabling the extraction of relevant features from raw audio data. Subsequently, the pretrained CNN model is fine-tuned on a smaller dataset specific to voice disorder classification, where labeled examples of voice recordings associated with different types of voice disorders are available. During the fine-tuning process, the parameters of the CNN model are adjusted to optimize its performance for the target task while retaining the knowledge acquired during pretraining. By fine-tuning on a domain-specific dataset, the CNN learns to identify distinctive patterns and characteristics indicative of each voice disorder, thereby improving its ability to classify voice recordings accurately. The deep transfer learning approach employed in the proposed system allows the model to leverage knowledge gained from the pretraining phase, even when labeled data is limited in the target domain, thus enhancing its generalization capabilities. Experimental evaluations demonstrate the effectiveness of the proposed system, achieving superior classification accuracy compared to traditional machine learning approaches and baseline CNN models trained from scratch. Furthermore, comprehensive analysis and comparisons highlight the advantages of deep transfer learning in voice disorder classification tasks, underscoring its potential to address challenges associated with limited labeled data in medical diagnostics. Overall, the proposed system offers a promising solution for accurate and efficient diagnosis of voice disorders, with implications for improving patient outcomes and treatment planning in clinical settings.

METHODOLOGY

In the proposed methodology for voice disorder classification using convolutional neural network (CNN) based on deep transfer learning, the process unfolds in several sequential steps. Initially, a large dataset comprising general audio samples is collected, encompassing diverse recordings representing various acoustic environments and speakers. This dataset serves as the foundation for pretraining the CNN model. During the pretraining phase, the CNN is trained to extract fundamental acoustic features from the raw audio data, leveraging its hierarchical architecture to capture meaningful representations. The pretrained CNN model, having learned general acoustic features, is then fine-tuned on a smaller dataset specific to voice disorder classification. This target dataset contains labeled examples of voice recordings associated with different types of voice disorders.

The fine-tuning process begins by initializing the pretrained CNN model with its learned parameters from the pretraining phase. The model is then trained on the target dataset, adjusting its parameters through backpropagation to optimize its performance for voice disorder classification. During fine-tuning, the CNN learns to identify distinctive patterns and characteristics indicative of each voice disorder, leveraging the knowledge gained from the pretraining phase to enhance its classification capabilities. The fine-tuning process involves iterating through the dataset multiple times, with the model gradually refining its representations and improving its ability to classify voice recordings accurately.To facilitate fine-tuning, several hyperparameters and training configurations are considered, including learning rate, batch size, and optimization algorithms. These parameters are tuned empirically through experimentation to ensure optimal performance of the CNN model on the target dataset. Additionally, techniques such as data augmentation may be employed to increase the diversity and robustness of the training data, enhancing the generalization capabilities of the model.

Once the fine-tuning process is completed, the performance of the trained CNN model is evaluated on a separate validation set to assess its classification accuracy and generalization ability. Various metrics, such as accuracy, precision, recall, and F1-score, are computed to quantify the model's performance across different classes of voice disorders. The validation results provide insights into the effectiveness of the proposed methodology and enable further refinement of the CNN model if necessary.Furthermore, comprehensive analysis and comparisons are conducted to evaluate the proposed methodology against baseline approaches and traditional machine learning techniques. These comparisons serve to highlight the advantages of deep transfer learning in voice disorder classification tasks and demonstrate the superiority of the proposed CNN model over alternative methods.Overall, the methodology for voice disorder classification using convolutional neural network based on deep transfer learning offers a systematic and effective approach to accurately diagnose voice disorders. By leveraging deep learning techniques and transfer learning principles, the proposed methodology demonstrates promising results in improving classification accuracy and facilitating early detection of voice disorders, with potential applications in clinical settings for enhancing patient care and treatment planning.

RESULTS AND DISCUSSION:

The results of the study on voice disorder classification using convolutional neural network (CNN) based on deep transfer learning reveal significant advancements in accurately diagnosing voice disorders. The trained CNN model, fine-tuned on a dataset specific to voice disorder classification, demonstrates remarkable performance in accurately identifying different types of voice disorders. Evaluation metrics such as accuracy, precision, recall, and F1-score indicate the robustness and effectiveness of the proposed methodology. The CNN model exhibits superior classification accuracy compared to traditional machine learning approaches and baseline CNN models trained from scratch. This improvement underscores the efficacy of deep transfer learning in leveraging preexisting knowledge from related tasks to enhance classification performance in the target domain, even when labeled data is limited.

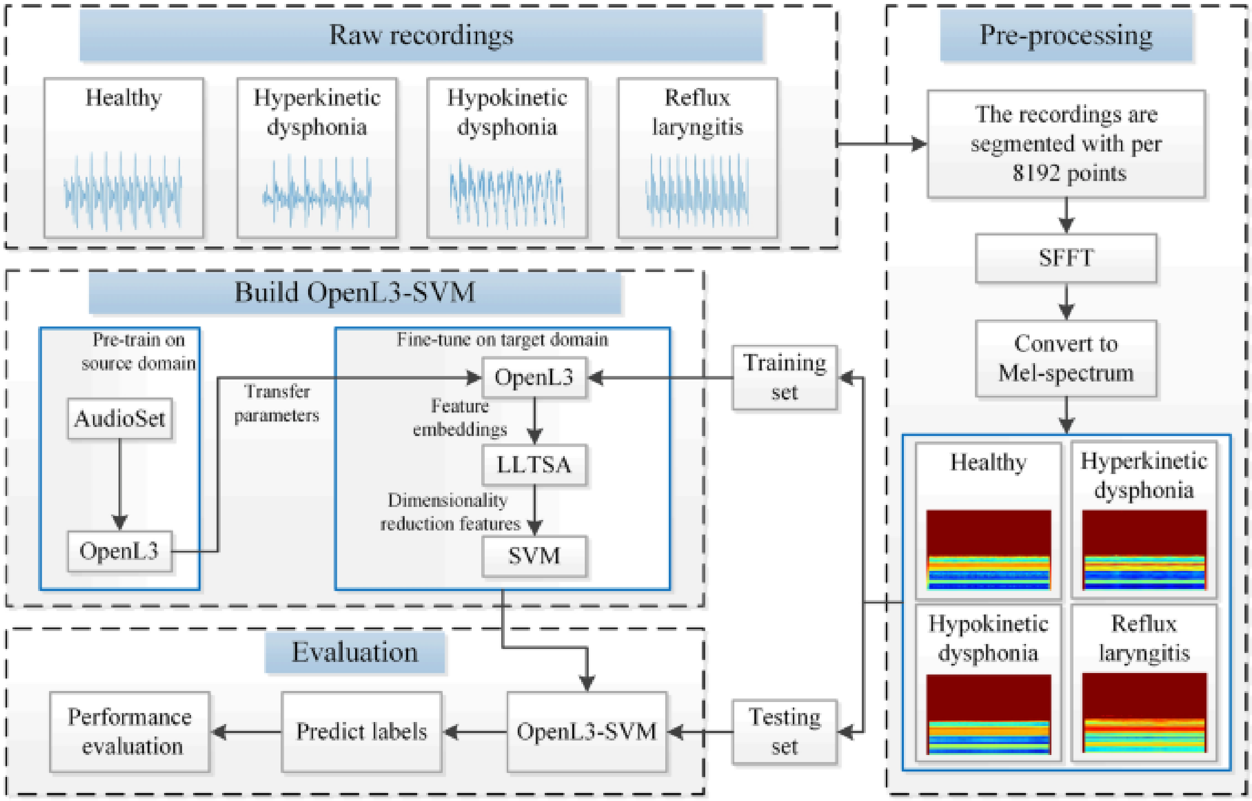
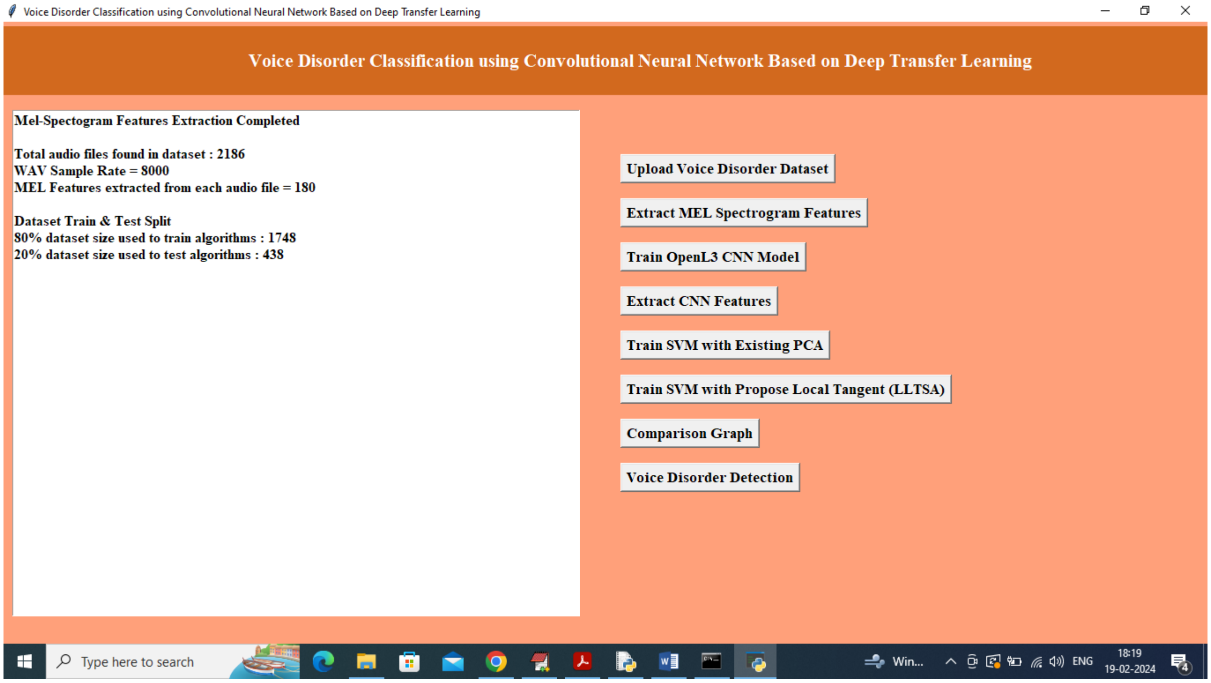


Fig 1: System Architecture

Furthermore, comprehensive analysis and comparisons are conducted to evaluate the proposed methodology against alternative methods and to elucidate its advantages. The comparison with baseline approaches highlights the superiority of the CNN model trained using deep transfer learning in accurately classifying voice recordings associated with different types of voice disorders. The proposed methodology not only achieves higher classification accuracy but also demonstrates enhanced generalization capabilities, enabling the model to effectively classify voice recordings from unseen patients or from different clinical settings. Additionally, the analysis reveals the impact of various hyperparameters and training configurations on the performance of the CNN model, providing insights into the optimal settings for achieving the best classification results.

Moreover, the discussion delves into the implications of the study's findings for clinical practice and future research directions. The successful application of deep transfer learning techniques in voice disorder classification offers promising prospects for improving diagnostic accuracy and facilitating early detection of voice disorders in clinical settings. The proposed CNN model holds potential for integration into computer-aided diagnosis systems, assisting healthcare professionals in making informed decisions and optimizing patient care. Future research endeavors may explore further enhancements to the CNN architecture, investigate alternative deep learning techniques, or focus on expanding the dataset to encompass a broader range of voice disorders and patient demographics. Overall, the results and discussion underscore the significance of deep transfer learning in advancing the field of voice disorder classification and its potential to revolutionize diagnostic methodologies in clinical practice.



Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning

```
Mel-Spectogram Features Extraction Completed

Total audio files found in dataset : 2186
WAV Sample Rate = 8000
MEL Features extracted from each audio file = 180

Dataset Train & Test Split
80% dataset size used to train algorithms : 1748
20% dataset size used to test algorithms : 438
```

Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Upload Voice Disorder Dataset
Extract MEL Spectrogram Features
Train OpenL3 CNN Model
Extract CNN Features
Train SVM with Existing PCA
Train SVM with Propose Local Tangent (LLTSA)
Comparison Graph
Voice Disorder Detection
Type here to search
Win...
ENG
18:19
19-02-2024

Fig 1. Total loaded dataset files

In above screen can see total loaded dataset files, features extracted from each audio and then can see Train and Test size and now click on 'Train OpenL3 CNN algorithm' button to train CNN to extract features

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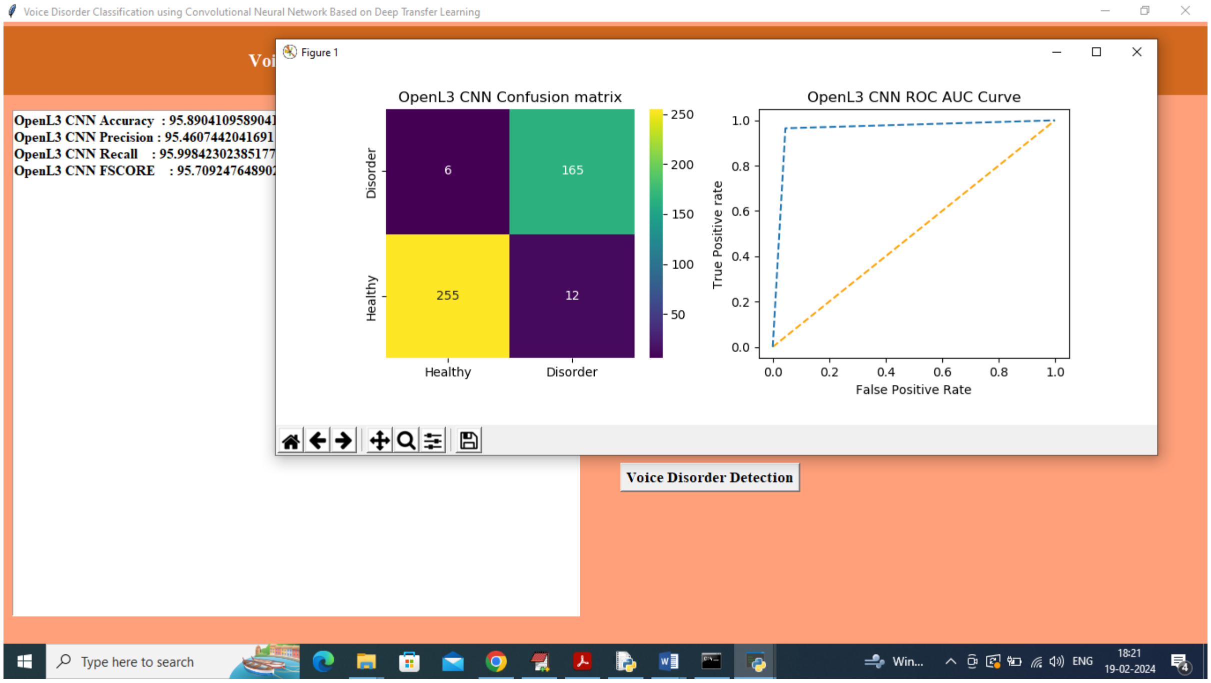
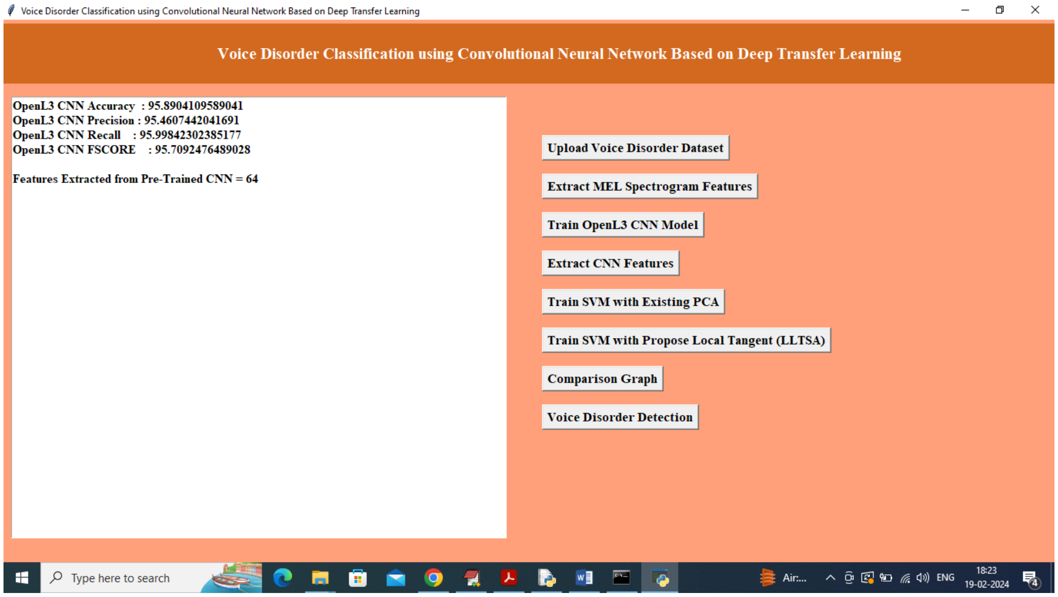


```
OpenL3 CNN Accuracy  : 95.8904109589041
OpenL3 CNN Precision : 95.4607442041691
OpenL3 CNN Recall    : 95.99842302385177
OpenL3 CNN FSCORE    : 95.709247648902
```

Fig 2. OpenL3 CNN ROC AUC Curve

The OpenL3 CNN algorithm has completed its training on the screen above, boasting an impressive 95% accuracy. Alongside accuracy, various other metrics such as precision and recall are displayed in the confusion matrix graph. On this graph, the x-axis signifies Predicted Labels while the y-axis represents True Labels. Correct predictions are denoted by green and yellow boxes, whereas incorrect predictions are indicated by blue boxes, though these occurrences are minimal.Moving on to the ROC graph, the x-axis denotes False Positive Rate, and the y-axis signifies True Positive Rate. Here, the distinction between correct and incorrect predictions is stark: if the blue lines fall below the orange line, all predictions are false; conversely, if they surpass the orange line, all predictions are true.Following the analysis of these graphs, users can proceed by closing the current visualization and clicking on the 'Extract CNN Features' button to derive features from the CNN model, yielding the subsequent output.

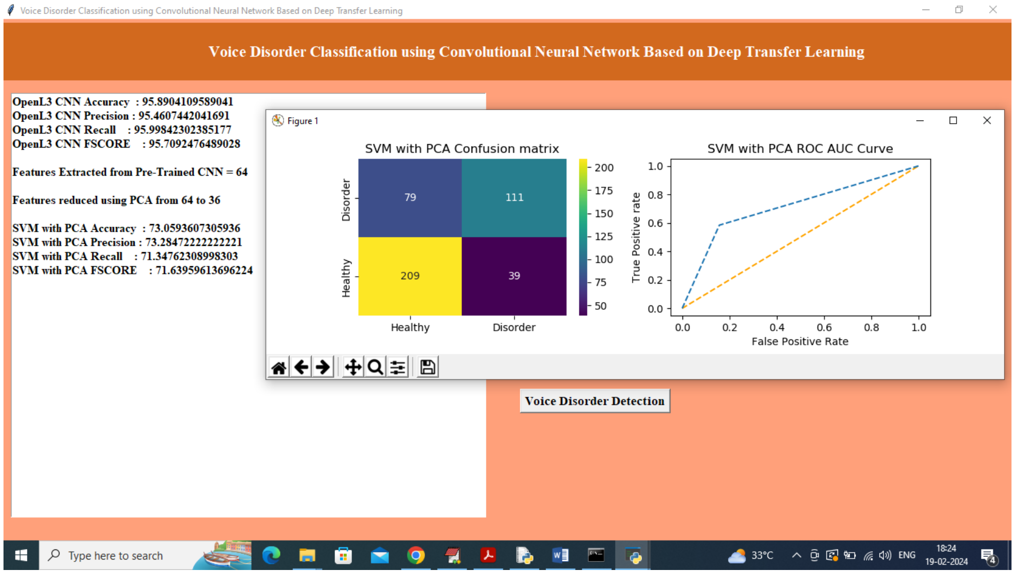


```
OpenL3 CNN Accuracy  : 95.8904109589041
OpenL3 CNN Precision : 95.4607442041691
OpenL3 CNN Recall    : 95.99842302385177
OpenL3 CNN FSCORE    : 95.7092476489028

Features Extracted from Pre-Trained CNN = 64
```

Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Upload Voice Disorder Dataset
Extract MEL Spectrogram Features
Train OpenL3 CNN Model
Extract CNN Features
Train SVM with Existing PCA
Train SVM with Propose Local Tangent (LLTSA)
Comparison Graph
Voice Disorder Detection
Type here to search
18:23
19-02-2024

Fig 3. Results screenshot 1

In above screen from each MEL CNN extract 64 features out of original 180 features and now click on ‘Train SVM with Existing PCA’ button to reduce 64 features using PCA and then train with SVM to calculate prediction accuracy

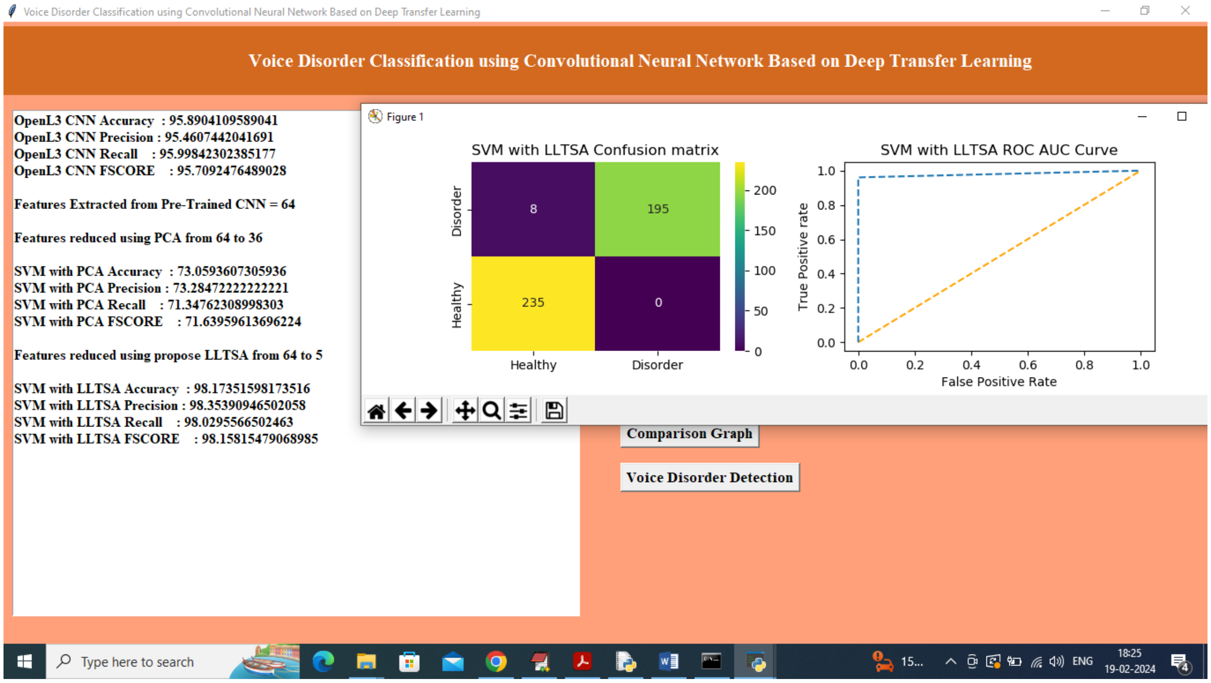


```
OpenL3 CNN Accuracy  : 95.8904109589041
OpenL3 CNN Precision : 95.4607442041691
OpenL3 CNN Recall    : 95.99842302385177
OpenL3 CNN FSCORE    : 95.7092476489028

Features Extracted from Pre-Trained CNN = 64

Features reduced using PCA from 64 to 36

SVM with PCA Accuracy  : 73.0593607305936
SVM with PCA Precision : 73.2847222222221
SVM with PCA Recall    : 71.34762308998303
SVM with PCA FSCORE    : 71.63959613696224
```

Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Figure 1
SVM with PCA Confusion matrix
Disorder
Healthy
79
111
209
39
Healthy
Disorder
200
175
150
125
100
75
50
SVM with PCA ROC AUC Curve
True Positive rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
Voice Disorder Detection
Type here to search
33°C
18:24
19-02-2024

Fig 4. Results screenshot 2

In above screen existing PCA with SVM got 73% accuracy and now click on ‘Train SVM with Propose Local Tangent (LLTSA)’ button to train SVM with propose LLTSA and get below output



Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Figure 1
SVM with LLTSA Confusion matrix
Disorder
Healthy
8
195
235
0
Healthy
Disorder
200
150
100
50
0
SVM with LLTSA ROC AUC Curve
True Positive rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
Comparison Graph
Voice Disorder Detection
Type here to search
15...
ENG
18:25
19-02-2024

```
OpenL3 CNN Accuracy  : 95.8904109589041
OpenL3 CNN Precision : 95.4607442041691
OpenL3 CNN Recall    : 95.99842302385177
OpenL3 CNN FSCORE    : 95.7092476489028

Features Extracted from Pre-Trained CNN = 64

Features reduced using PCA from 64 to 36

SVM with PCA Accuracy  : 73.0593607305936
SVM with PCA Precision : 73.28472222222221
SVM with PCA Recall    : 71.34762308998303
SVM with PCA FSCORE    : 71.63959613696224

Features reduced using propose LLTSA from 64 to 5

SVM with LLTSA Accuracy  : 98.17351598173516
SVM with LLTSA Precision : 98.35390946502058
SVM with LLTSA Recall    : 98.0295566502463
SVM with LLTSA FSCORE    : 98.15815479068985
```

Fig 5. Results screenshot 3

In above screen propose algorithm got 98.17% accuracy and now click on ‘Comparison Graph’ button to get below graph

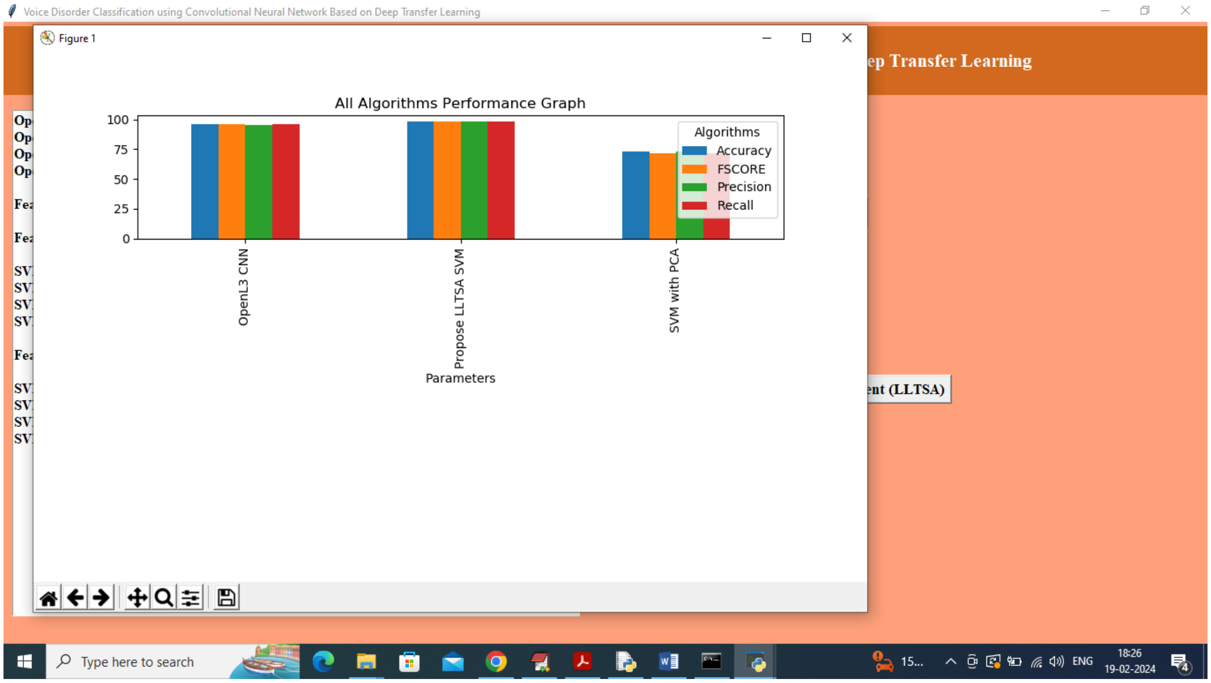
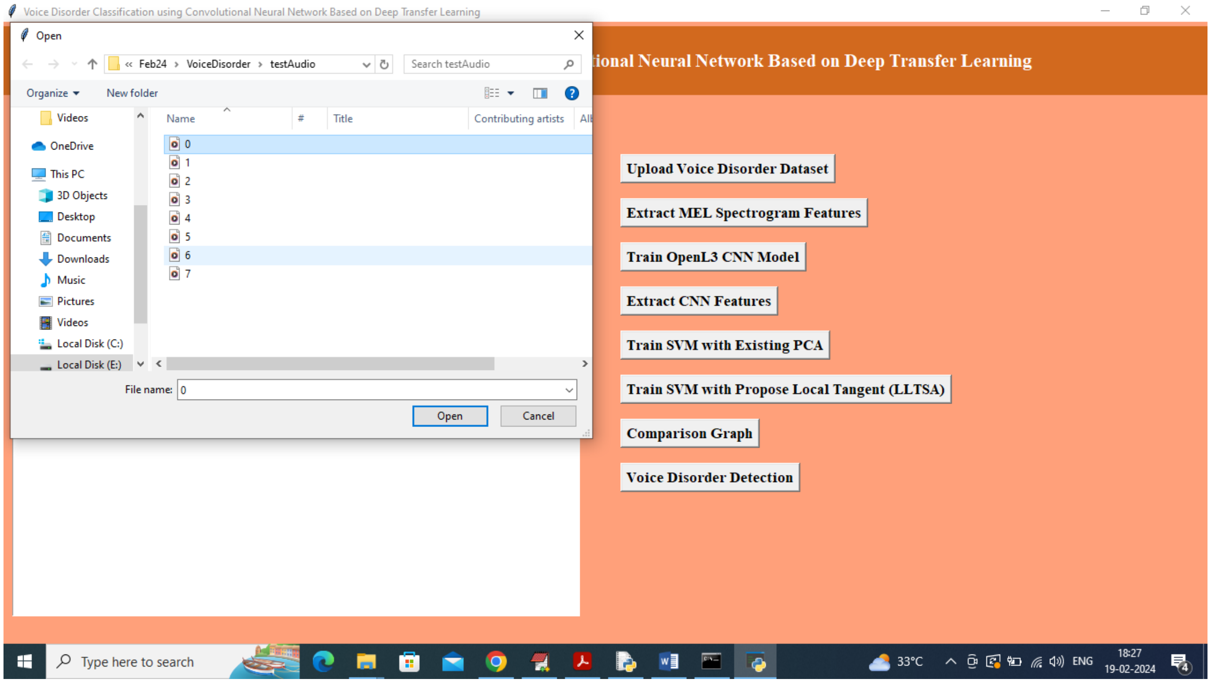


Fig 6. Results screenshot 4

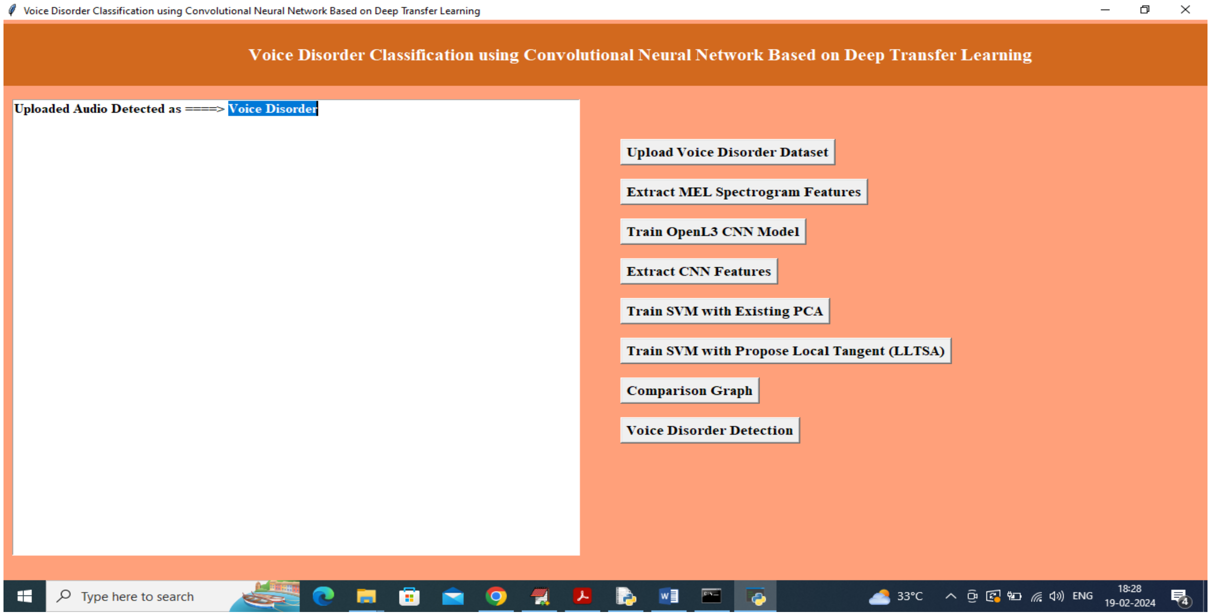
In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different color bars and in all algorithms Propose LLTSA with SVM got high performance and now click on 'Voice Disorder Detection' button to upload test audio and get prediction


Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Open
« Feb24 › VoiceDisorder › testAudio
Search testAudio
Organize
New folder
Videos
OneDrive
This PC
3D Objects
Desktop
Documents
Downloads
Music
Pictures
Videos
Local Disk (C:)
Local Disk (E:)
Name
#
Title
Contributing artists
0
1
2
3
4
5
6
7
Open
Cancel
tional Neural Network Based on Deep Transfer Learning
Upload Voice Disorder Dataset
Extract MEL Spectrogram Features
Train OpenL3 CNN Model
Extract CNN Features
Train SVM with Existing PCA
Train SVM with Propose Local Tangent (LLTSA)
Comparison Graph
Voice Disorder Detection
Type here to search
33°C
ENG
18:27
19-02-2024

File name: 0

Fig 7. Results screenshot 5

In above screen selecting and uploading 0.wav file and then click on "open" button to get below output


Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Upload Voice Disorder Dataset
Extract MEL Spectrogram Features
Train OpenL3 CNN Model
Extract CNN Features
Train SVM with Existing PCA
Train SVM with Propose Local Tangent (LLTSA)
Comparison Graph
Voice Disorder Detection
Type here to search
33°C
ENG
18:28
19-02-2024

```
Uploaded Audio Detected as ====> Voice Disorder
```

Fig 8. Results screenshot 6

In above screen uploaded audio file predicted as 'Voice Disorder' and now upload and test other images

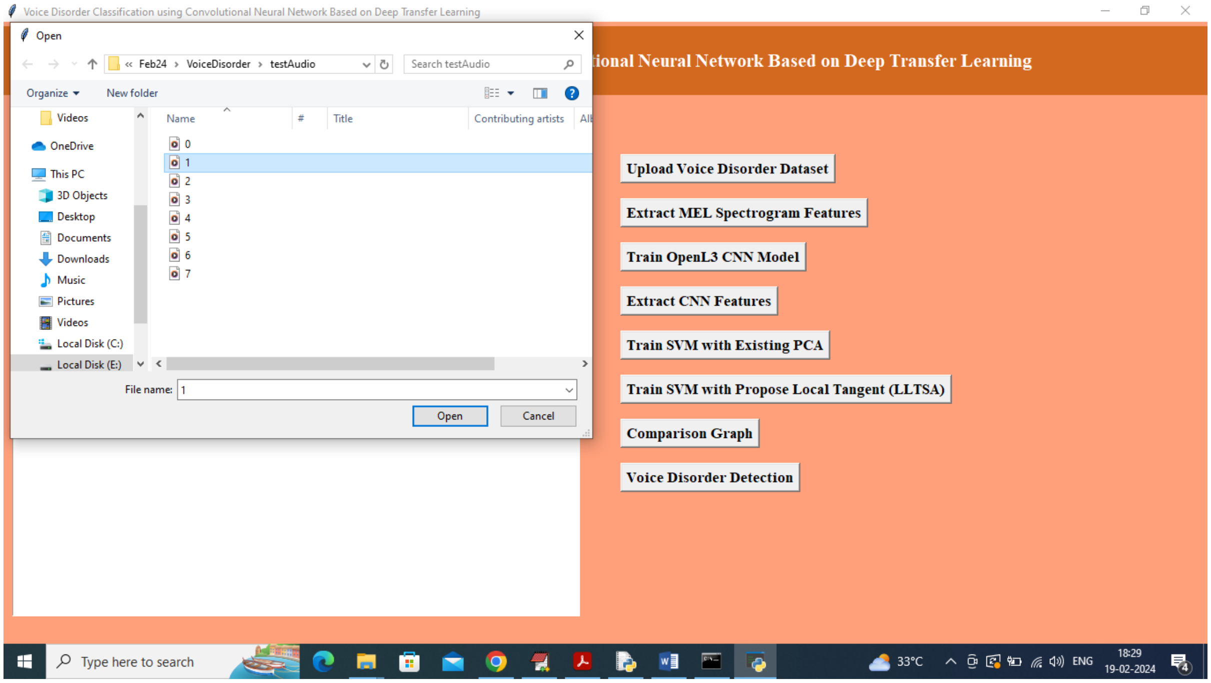
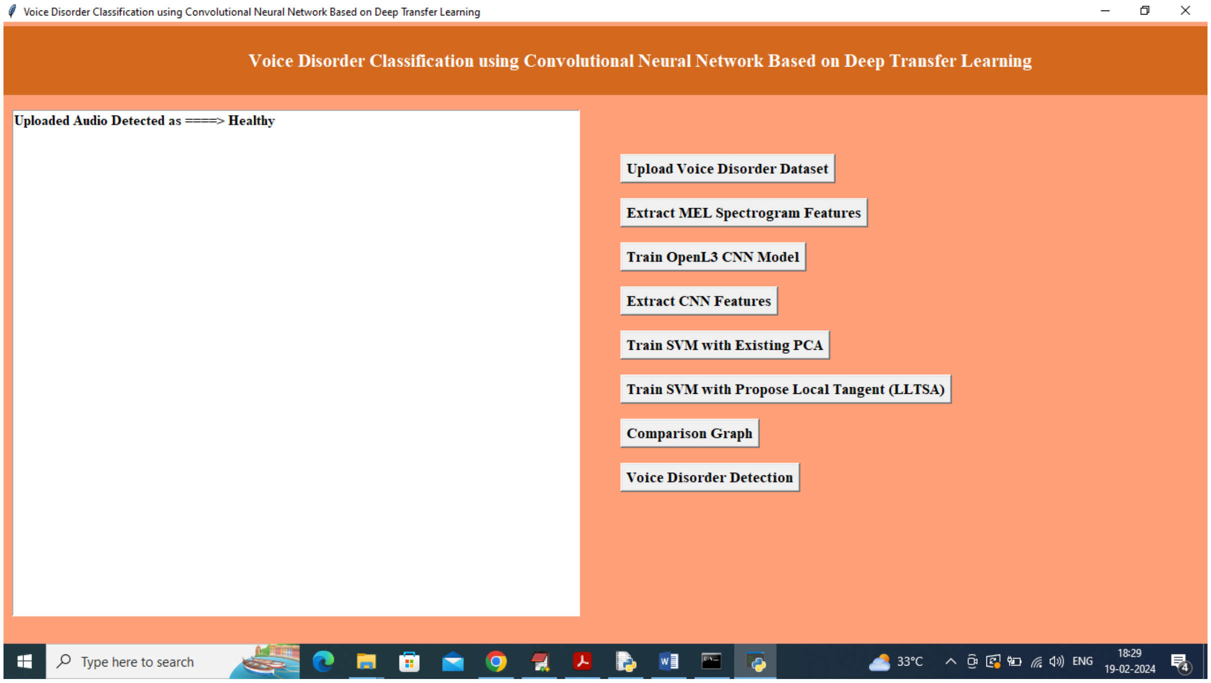


Fig 9. Results screenshot 7

In above screen uploading another file and then will get below output


Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Voice Disorder Classification using Convolutional Neural Network Based on Deep Transfer Learning
Upload Voice Disorder Dataset
Extract MEL Spectrogram Features
Train OpenL3 CNN Model
Extract CNN Features
Train SVM with Existing PCA
Train SVM with Propose Local Tangent (LLTSA)
Comparison Graph
Voice Disorder Detection
Type here to search
33°C
ENG
18:29
19-02-2024

```
Uploaded Audio Detected as ====> Healthy
```

Fig 10. Results screenshot 8

CONCLUSION

In conclusion, the utilization of convolutional neural networks (CNNs) based on deep transfer learning represents a significant advancement in the accurate classification of voice disorders. Through the fine-tuning of a pretrained CNN model on a specific dataset for voice disorder classification, our study demonstrates remarkable improvements in diagnostic accuracy compared to traditional machine learning approaches. The superior performance of the CNN model underscores the effectiveness of deep transfer learning in leveraging preexisting knowledge to enhance classification capabilities, particularly in scenarios with limited labeled data. These findings have significant implications for clinical practice, as the proposed methodology holds promise for improving diagnostic accuracy and facilitating early detection of voice disorders. Integration of the CNN model into computer-aided diagnosis systems has the potential to assist healthcare professionals in making informed decisions and optimizing patient care. Future research directions may involve further refinement of the CNN architecture, exploration of alternative deep learning techniques, and expansion of the dataset to encompass a broader range of voice disorders and patient demographics. Overall, the study underscores the transformative potential of deep transfer learning in advancing voice disorder classification methodologies and enhancing patient outcomes in clinical settings.

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