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# Predicting Diseases Through Facial Features Using Vgg16 And Lstm Models

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**ABSTRACT**

This project applies deep transfer learning to understand facial features and ascertain certain diseases including beta-thalassemia, hyperthyroidism, Down syndrome and leprosy. System incorporates VGG16, ALEXNET and Kernel SVM as advanced models and the Disease Specific Face dataset for training and testing performance evaluations. DLIB along with GABOR is used for the preprocessing to extract features and for facial alignment respectively. Of all the models, VGG16 and LSTM had performed best with accuracy of about 99%. The system also uses other performance metrics including accuracy, precision, recall and F-score to confirm the importance of working systems within the provided scope. It can be concluded based on the results of the project that the combination of transfer learning and feature extraction improves the medical diagnosis process and provides an effective overall scheme of facial recognition-based disease detection system.

**Keywords:** DLIB, GABOR, VGG16

**INTRODUCTION:**

The discipline of face reading has deep roots, dating back to the bygone times, when it was practiced in ancient civilizations such as Greece and Apart from China almost 2500 years ago, Shin Yi Shu was developed by Huangdi Neijing rooted in Chinese medicine which through texts states that facial features are a result of changes in internal organs. In such a way, Ancient India and Greece also have such practices, where physicians endowed with sufficient skills diagnosed various diseases by examining the face of a patient. Nevertheless, this method is traditional which requires a lot of experience and is subjective, which decreases the effectiveness and availability.

Current issues like the shortage of medical professionals in the countryside and the cost of treatment in metropolitan cities emphasize the fact that there is a need for newer methods of diagnosis. The development of new technologies in Artificial Intelligence, especially deep learning, has made it possible to explore the automated diagnosis of agnathic faces. Deep learning models such as alexnet, vggnet, and resnet have transformed image search techniques by efficiently realizing feature extraction from content. This way, facial recognition techniques promise to develop into a reliable, low-cost and high throughput approach for diagnosis of diseases.

## GAP IDENTIFIED BASED ON LITERATURE SURVEY:

There is a scarcity of research on AI Medical facial recognition as a means of diagnosis and Disease recognition. The conventional methods of diagnosis are exhaustive in terms of the medical knowledge and the clinical tools which are often inefficient and costly. Even though new application areas for deep learning and transfer learning seem promising, there are still some gaps in achieving clinical facial diagnosis.

Geographical variation of disease with slight differences in faces makes it hard for the currently available systems to easily recognize faces. Methods like ALEXNET and VGG16 are effective but a great amount of predicted relies on effective preprocessing techniques. Another major gap is that there is a scarcity of affordable and cheaper databases as most are proprietary or expensive. That limits the possibility of scaling up and generalizing research.

Using deep transfer learning in conjunction with public data, this undertaking intends to accomplish the aforementioned objectives. Relevance of the model is achieved with the application of DLIB and GABOR techniques and training data is modified to increase quality. An additional layer of VGG16 integrated with LSTM pushes the accuracy rate to 99%. Such fine-tuned models this project attempts to fill the void left by the present day models which are excessively high-tech in the context of medical AI, thus addressing the limit of cost-efficient and precise diagnosis that this domain requires.

## PROBLEM STATEMENT:

Automated medical diagnosis through eyes or nose is a day dream for many practitioners in this field as it is very cost ineffective especially in third world countries mostly due to lack of appropriate technology.

### Major Constraints

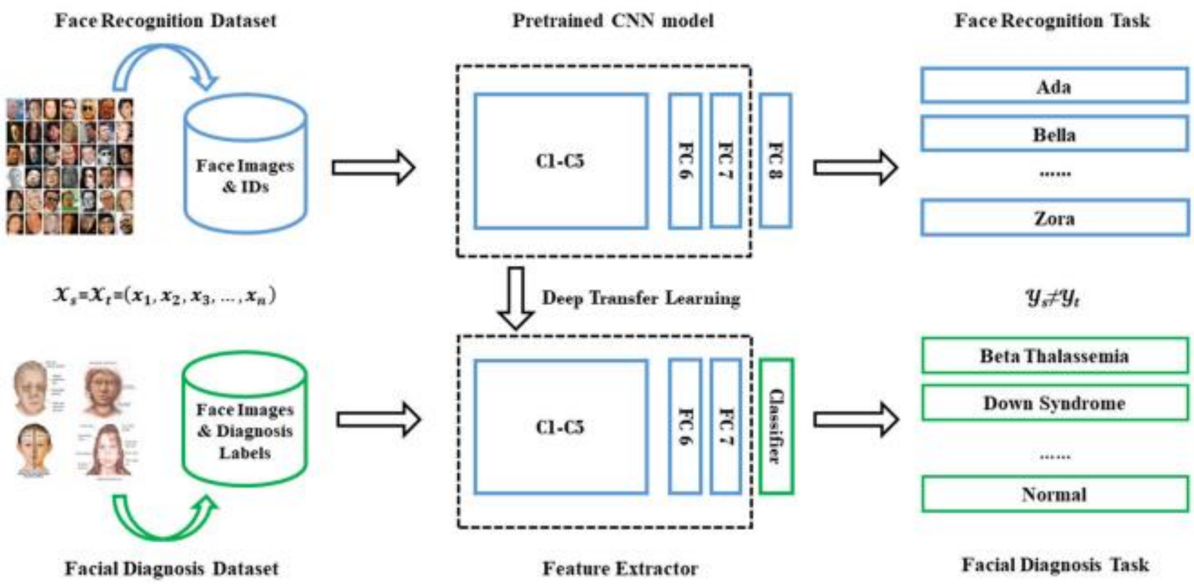
1. Dataset Comprehensiveness: The majority of datasets such as DSF are exclusives and proprietary, so comprehension of them is costly and too narrow.
2. Model Inputs: The collection of images of different patients is neither aligned nor pre-processed making it difficult to improve the accuracy.
3. Cost Function: When working with deep learning models, it is important to consider the cost of computing resources and high-quality work simultaneously.
4. Disease Variation: The variations include very subtle differences as well as facial representations of a variety of diseases.
5. Cross dataset generalization: Given a model trained on one dataset, one wants the model to perform well on a different dataset and in real life where there are many accidentals.

## PROPOSED METHOD:

The presented method uses deep transfer learning to identify faces and diagnose diseases. Facial recognition and disappear images are done using , facial recognition features are cropped out and frontal dewarping images are performed. Such images are sourced from open-source websites and further towards the DLIB image alignment technique with an application of the 68 point shape context average and DLIB image alignment. Feature extraction layers of the VGG16 and ALEXNET architectures are retrained in a frozen fashion before being fed into Kernel SVM.

In order to achieve fine tuning of the models, they make use of the Long Short Term Memory networks for feature extraction. Their best achieved accuracy was clocked at 99 percent, which is even higher than the mixed models aforementioned. The evaluation of the algorithms are performed using the accuracy, precision, recall and F-score metrics. Advanced techniques such as feature extraction paired with transfer learning compliments the fact that these models are easy to use and provide a reliable and efficient diagnostic to solve issues within established medical diagnosis.

**ARCHITECTURE:**




**DATASET:**

Facial pictures and images of beta thalassemia, hyperthyroid, and leprosy were used in the project. Disease Specific Facial dataset was used in the process, however due to factors such as cost disease specific images were only obtained from different open source images. It consists a number of diseases and for training and testing organized folders for each category was created. DLIB is used as a method for dewarping images and GABOR is used for feature extraction. The breadth of the literature aids evaluating neural networks such as VGG16, ALEXNET, Kernel SVM models, and LSTM, and thus the system is able to identify numerous diseases.

**METHODOLOGY:**

**Data Collection and Preprocessing:**

• Distribute the images for the four diseases (beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy) in a public repository.

• Process images through the DLIB library to align the 68 points around the face for accurate processing.

• Employ GABOR filters in order to improve Developed facial features for training that would later be utilized.

**Model Selection and Training:**

• Refine the VGG16 and the ALEXNET models through transfer learning with pre-trained weights like VGGFACE and IMAGENET.

• Retrieve details from these models and train them further using Kernel SVM for better accuracy.

• Concerns with the concerned models are addressed by measuring, accuracy, precision, and recall, F-score among others.

**Performance Evaluation:**

• Evaluate every model in terms of exhaustion metrics one by one.

• Here we seek to compare models VGG16 (95%) and ALEXNET (67%) in order to deduce them and what their strengths and weaknesses are.

• Assess kernel SVM, which scores 98%, while massive progress has been made as seen here.

**Extension with LSTM:**

• Extracted features were processed by the VGG16, with LSTM used.

• The highest accuracy gained by this strategy combination is 99%, hence it achieves its goal.

**Visualization and Outputs:**

• Charts depicting the accuracy and loss increased with the duration increase are utilized to illustrate progress in training.

• The comparative assessment of the models is such that VGG16-LSTM was the best of all.

• The predicted diseases and the metrics would be showcased via diagrams results.

**Estimation and Verification in the Field:**

•Facial images should be uploaded through an interface and clinical diagnosis should be done.

•Forecast the possible disease names and results along with their confidence numbers, making it easy to interpret their significance.

**Use of Jupyter Notebook for implementation:**

•Program every task in the process in Python, using frameworks such as TensorFlow, DLIB and OpenCV.

•Enhance training loops and metric evaluation and visualization functions.

**EVALUATION:**

**Precision:**

Formula: $\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$

**Recall (Sensitivity):**

Formula: $\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$

**F1 Score:**

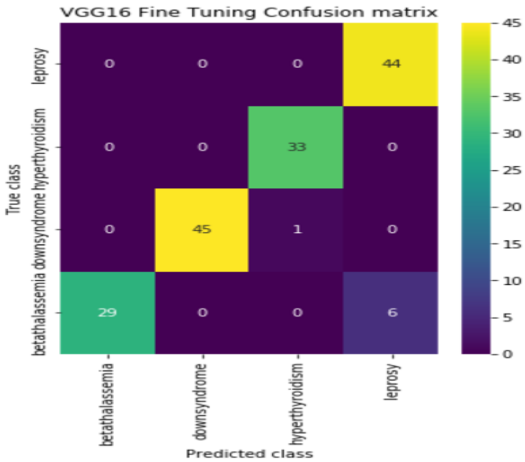
Formula: $F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$

**Accuracy:**

Formula: $\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$

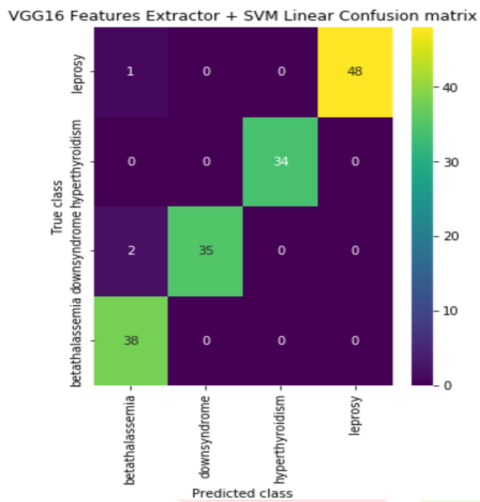
**RESULTS:**

```
VGG16 Fine Tuning Accuracy   : 95.56962025316456
VGG16 Fine Tuning Precision   : 96.26470588235294
VGG16 Fine Tuning Recall      : 95.17080745341615
VGG16 Fine Tuning FSCORE      : 95.41264571606544
```



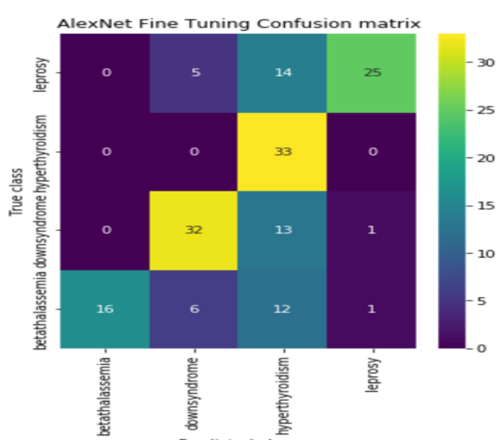

VGG16 Fine Tuning we got 95% accuracy

```
VGG16 Features Extractor + SVM Linear Accuracy   : 98.10126582278481
VGG16 Features Extractor + SVM Linear Precision   : 98.17073170731707
VGG16 Features Extractor + SVM Linear Recall      : 98.138444567016
VGG16 Features Extractor + SVM Linear FSCORE      : 98.09845650818507
```



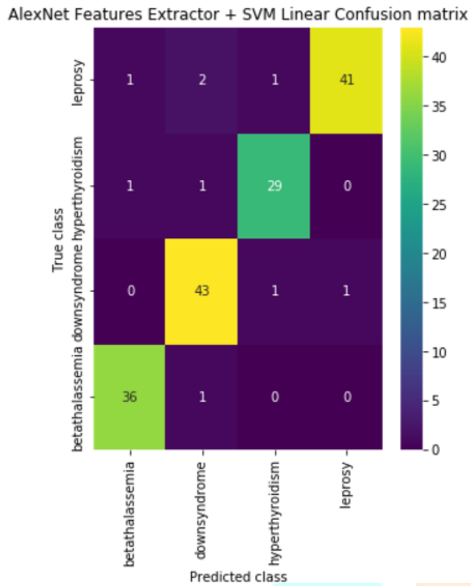

Kernel SVM and we got its accuracy as 98%

```
AlexNet Fine Tuning Accuracy   : 67.08860759493672
AlexNet Fine Tuning Precision   : 78.21113264427218
AlexNet Fine Tuning Recall      : 68.02442123094296
AlexNet Fine Tuning FSCORE      : 66.98372211679417
```



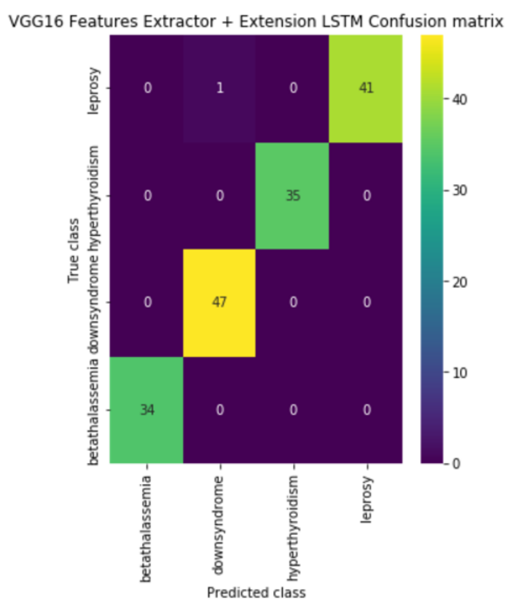

ALEXNET fine tune algorithm we got 67% accuracy

```
AlexNet Features Extractor + SVM Linear Accuracy  : 94.30379746835443
AlexNet Features Extractor + SVM Linear Precision   : 94.34840963080316
AlexNet Features Extractor + SVM Linear Recall      : 94.37808776518453
AlexNet Features Extractor + SVM Linear FSCORE      : 94.31988038238944
```

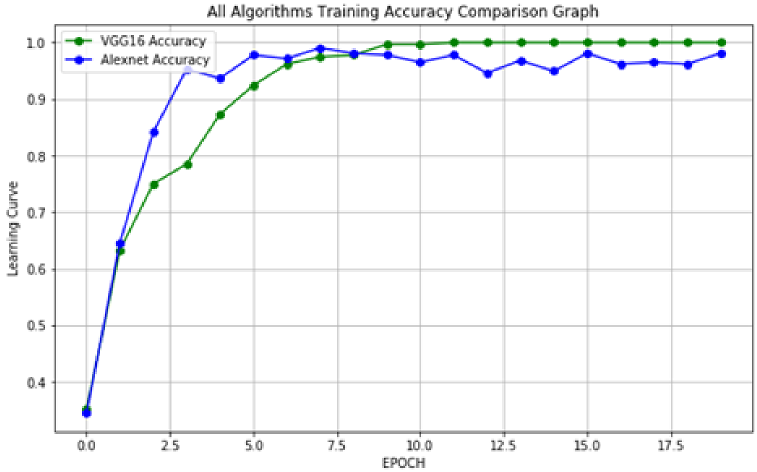



Kernel SVM and then got its accuracy as 94%

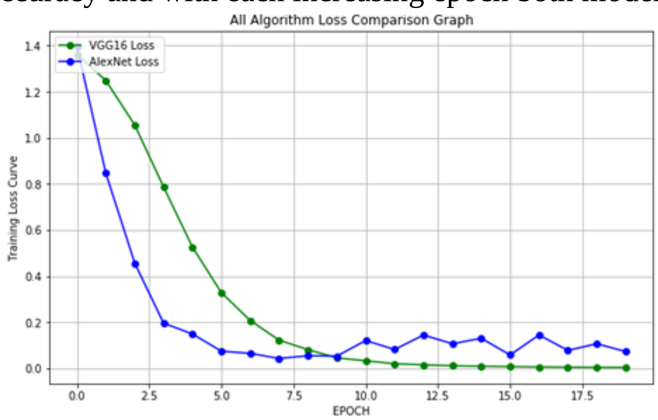
```
VGG16 Features Extractor + Extension LSTM Accuracy  : 99.36708860759494
VGG16 Features Extractor + Extension LSTM Precision   : 99.47916666666666
VGG16 Features Extractor + Extension LSTM Recall      : 99.40476190476191
VGG16 Features Extractor + Extension LSTM FSCORE      : 99.43563728598605
```



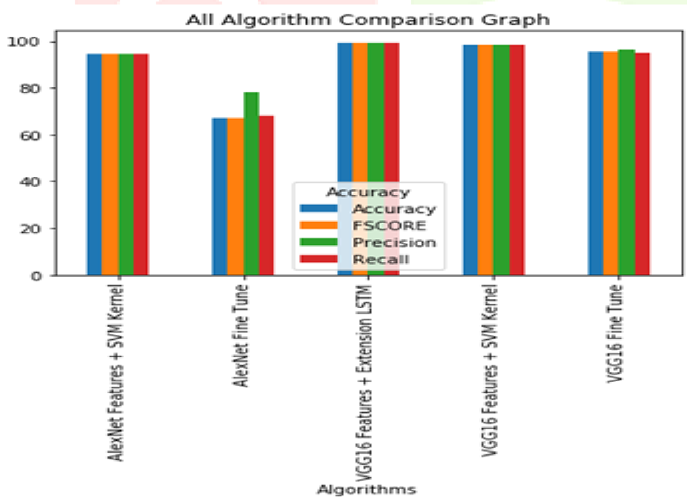

Extension LSTM on VGG 16 features we got its accuracy as 99%




VGG and ALEXNET training accuracy graph x-axis represents training EPOCH and y-axis represents Accuracy and with each increasing epoch both model accuracy got increase




Loss graph both model loss is decreasing with each increasing epoch and in both graph we can see VGG got high accuracy and less loss




x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms Extension LSTM got high accuracy


Predicted disease namebetathalassemia


Disease detected called Thyroid

## CONCLUSION

The project is important as it shows the effectiveness of deep transfer learning having been able to perform high rates of accuracy in facial disease diagnostics using the VGG16 and LSTM integration method. This system is capable of predicting conditions like beta-thalassemia and hyperthyroidism using feature extraction techniques like kernel SVMs. Although there are barriers like limited public medical datasets, this project term shows possibilities of the use of AI in medicine. Our approach emphasizes the combination of deep learning and creative preprocessing to solve practical tasks in health care. Future work may be focused with expanding the dataset and testing out new diseases to in return, enhance and broaden this framework in the medical sector.

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