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Automated Detection of Pulmonary Fibrosis using Transfer Learning Models

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Abstract— **Pulmonary Fibrosis which is a chronic lung disease demands prompt diagnosis for effective management. This project develops an automated system using deep learning for feature extraction and machine learning for classification, reducing reliance on manual assessments. In this context, we use InceptionV3 for feature extraction, VGG19 for feature extraction, and MobileNetV2 for feature extraction as they are constantly successful and able to detect fine-grained patterns from medical images. The extracted features are further analyzed with popular machine learning techniques including but not limited to Random Forest and SVM. This has been such a break through because the new hybrid model, leads to a faster diagnosis even if it is comparatively more accurate, than the previously used models. The system's performance is evaluated using accuracy, precision, recall, and F1-score. Integrated into a Flask-based web application, it enables quick and accurate Pulmonary Fibrosis diagnosis, aiding timely treatment and better patient outcomes.**

Index Terms— Pulmonary Fibrosis, Diagnosis, Deep Learning Machine Learning, CT Scan, Feature Extraction, Web Application.

I. INTRODUCTION

Early diagnosis of pulmonary fibrosis is important so as to ensure that proper management is made and thus enhance prognosis of the illness. Unfortunately, early diagnosis of the disease is very difficult because the symptoms are vague and there is a lack of highly specific diagnostic methods. At the moment, diagnosis of pulmonary fibrosis employs a clinical approach, pulmonary function tests, and blood tests, imaging include (high-resolution computed tomography or HRCT) and in some cases lung biopsy. Although patterns of fibrosis, in particular, can be determined utilizing HRCT scans, the analysis of the scans themselves may not be entirely easy and requires much time and skill.

The authors believe that the development of DL as a type of AI can potentially revolutionize the ways of diagnosing and treating pulmonary fibrosis. DL algorithms can learn and recognize a large amount of medical data, for examples, imaging data, and discover the existing patterns and features impossible to detect by clinicians. This may result in increased accuracy and efficiency in making diagnosis and subsequent treatment since patient profiles inside electronic health record systems will be known.

II. LITERATURE REVIEW

Mohanty et al. (2020) [1] In their perspective piece titled, "In Vivo Assessment of Pulmonary Fibrosis and Pulmonary Edema in Rodents Using Ultrasound Multiple Scattering," the authors investigated how ultrasound might be useful for diagnosing PF. For this reason, the participants postulated that alteration in lung microarchitecture due to PF can be quantified via the scattering of the ultrasound waves. In an experiment with rat models, by seeing how PF changed the scattering of light through thickened alveolar walls , Kong could distinguish between normal and fibrotic lungs. It reveals potential of a non-invasive diagnostic solution for fibrosis in clinical applications with this novel concept.

In their paper, Shehab et al. (2020) [2] came up with a new method in which they utilized EfficientNet and QR to predict the Pf's progression. In turn, when training on the OSIC dataset, the authors showed that this model surpassed previous ones in terms of PF progression prediction, based on the Laplace-Log-Likelihood score. This paper shows how Machine Learning models, such as EfficientNet, can help in prognosis and indicating of prognostic results to guide the treatment process.

OSIC_Dataset Mandal et al. (2020) [3] In their study known as, "Incremental Machine Learning and AI its application among several models to predict decline in lung functions of patients with Idiopathic Pulmonary Fibrosis," Mandal at al. presented prediction analysis of the deterioration in the IPF patients as derived from OSIC dataset. They used forced vital capacity (FVC) in particular, which is a spirometer based parameter. Their work provided insights into early interventions in the treatment of PF and established that use of ML models to predict lung images presuming the severity of illness would also support management in healthcare.

Mento et al. (2020): [4] This work focuses on the QLUS for diagnosis of pulmonary fibrosis and calls for more quantitative approaches to the diagnosis process. The authors used a multifrequency imaging in ultrasound images from 26 individuals, yielding 92% sensitivity and specificity of differentiating pulmonary fibrosis.

Mento et al. (2020): [5] In a related work, the authors describe a quantitative approach based on multifrequency analysis of B-lines to distinguish pulmonary fibrosis: the sensibility of 100% and specificity of 90%. Such processes underline the possibilities of using more sophisticated techniques in the course of ultrasound as a source of rather accurate diagnostics data.

Earle and Al-Khassaweneh (2021): [6] Here, the authors describe a method for the lung capacity estimation in the pulmonary fibrosis patients based on the CT scan data and the machine learning. The present work included 172 patients and demonstrated that CT scans are valuable to detect the lung damage, and the conventional use of spirometry tests often causes difficulties for patients with impaired lung function. The authors confronted the problem of identifying the lung tissue using Hounsfield Units and concluded that this was insufficient; they questioned the accuracy of the present day approaches.

Glotov and Lyakhov (2021): [7] Regarding the issue of prognosis of pulmonary fibrosis progression this article focuses on the problem of accurate prediction of individual patient outcomes with the help of machine learning approaches. The authors present an idea for employing the four machine learning algorithms helps to predict the evolution of pulmonary fibrosis relying on MLC and note an increased efficacy in comparison with conventional approaches while stressing on the applicability of the improvement of clinical trial designs.

In this article, Yu et al. (2021) [8] suggested "Mga-Net": "Multi-Scale Guided Attention Models for an Automated Diagnosis of Idiopathic Pulmonary Fibrosis (IPF)." This method exposes an unprecedented multi-scale architecture for attention, MGA-Net. MGA-Net can achieve pretty high AUC scores on the high-resolution CT images that have clear identification of the lung lesion areas related to IPF. The significance of introducing guided attention mechanisms to increase the accuracy and interpretability of automated diagnostic systems for PF is what the current research claims.

Santiago-Fuentes et al. (2021): [9] The focus of this study is cardiovascular and respiratory coupling in IPF subjects, especially the acute response to oxygen therapy. The authors discovered that supplemental oxygen affected autonomic nervous system regulation in IPF patients and also identified the appropriate approach for alleviating symptoms.

X. Yu, Y. Zhang, L. Li, J. Han, and Z. Zhou (2022) [10]-"Detection of Idiopathic Pulmonary Fibrosi Lesion Regions Based on Corner Point Distribution" Deals with two-stage methods proposed by the authors Yu et al. to detect IPF lesions in x-ray CT. The method used for this study was firstly of candidate lesion detect followed by classification. It was found that the proposed method is a good performer juxtaposed with traditional k-means aggregator methods and could be a competent contender for executing the desired function of automatically detecting IPF lesions and thereby lessening radiologist duties.

Carvalho et al. (2023): [11] This paper presents domain generalization approaches for recognizing pulmonary fibrosis through deep learning models. The authors introduce a new approach to address the issue of internally validating models for changes in radiation dose and achieves significant improvement of F1 score which leads to increasing the effectiveness of the automatic diagnosis procedures.

In their paper, Shehab et al. (2023) [12] came up with a new method in which they utilized EfficientNet and QR to predict the Pf's progression. In turn, when training on the OSIC dataset, the authors showed that this model surpassed previous ones in terms of PF progression prediction, based on the Laplace-Log-Likelihood score. This paper shows how Machine Learning models, such as EfficientNet, can help in prognosis and indicating of prognostic results to guide the treatment process.

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Mentor et al. [14] The study conducted in this paper focuses on a Q-learning neural network for analysis in pulmonary fibrosis and suggests the use of algorithms for diagnosis. The authors took ultrasound images of 26 individuals using multifrequency imaging, achieving 92% sensitivity and specificity in identifying pulmonary fibrosis.

In their paper, Shehab et al. (2023) [15] came up with a new method in which they utilized EfficientNet and QR to predict the Pf's progression. In turn, when training on the OSIC dataset, the authors showed that this model surpassed previous ones in terms of PF progression prediction, based on the Laplace-Log-Likelihood score. This paper shows how Machine Learning models, such as EfficientNet, can help in prognosis and indicating of prognostic results to guide the treatment process.

III. METHODOLOGY

Another approach in detecting pulmonary fibrosis utilizing CT images applies a two-step methodology that combines the best of deep-learning feature extraction techniques with machine based classification. Using InceptionV3, VGG19, MobileNetV2, Random Forest, and Support Vector Machine (SVM) classifiers, the performance for both accuracy and computational demands would be kept in equilibrium. This chapter proposes a brief overview of the proposed system, and it identifies different constituent factors/phases of the proposed system as shown in Figure 1.

A. Data Preprocessing

However, preprocessing is highly important before feeding CT images to the deep learning models since the dataset must be cleaned and normalized first. Preprocessing includes:

- Resizing and Normalization: CT images are normalized for input to deep learning models where the input dimensions for Inception V3, VGG19, and Mobile Net V2 is 224*224 pixels. Standardization is used to normalize pixel values in order to help enhance the

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performance of the model.

- Data Augmentation: There is a scarcity of labeled medical data hence; several data augmentation techniques are used in an attempt to overcome this issue. Here we have rotation, zooming, flipping and shifting to make the model sample bigger and make the model ready to encounter different variations in the data.
- Noise Reduction: In CT images, there is usually noise which influences the training of the model in learning some of the features to predict its output. Gaussian filtering or median filtering is used to reduce noises on the input data so as to enhance the quality of the input data.

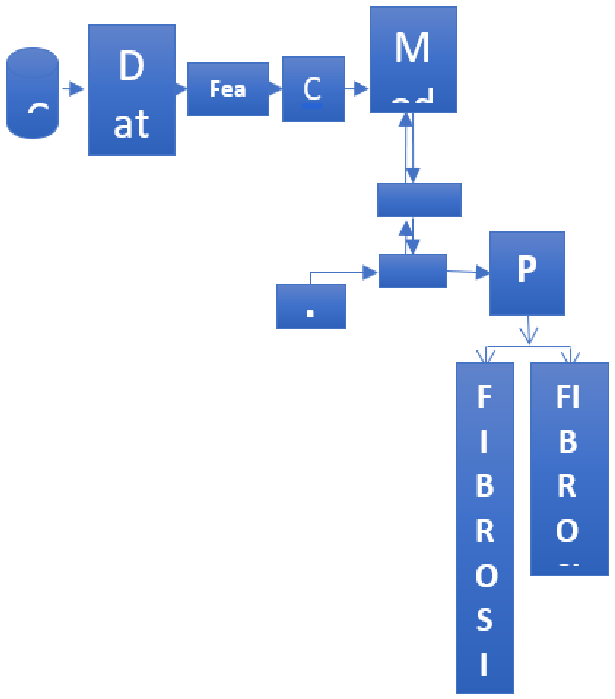

Figure 1. System Architecture

B. Feature Extraction Using Deep Learning Models

For feature extraction, three pre-trained convolutional neural network (CNN) models are used: InceptionV3, VGG19, and MobileNetV2. These models are selected for their ability to capture complex patterns in medical images and their proven success in image classification tasks. Each of these models is fine-tuned on the Pulmonary Fibrosis dataset, and the following steps are performed:

- InceptionV3: Known for its ability to handle complex features using its inception module, this model extracts multi-scale features from the input CT images. The architecture enables the network to capture both global and local image features, making it suitable for identifying subtle patterns in lung fibrosis.
- VGG19: VGG19 is a deeper network that uses 19 layers to capture hierarchical features. It is particularly effective in medical imaging tasks where spatial relationships between pixels are crucial. VGG19 extracts detailed features such as fibrosis patterns, honeycombing, and reticulation from the lung tissues.
- MobileNetV2: MobileNetV2 is a lightweight and efficient model, designed for mobile and resource-constrained environments. It uses depthwise separable convolutions, which reduce the computational complexity while maintaining performance. This model is ideal for real-time applications where faster predictions are needed without sacrificing too much accuracy.

After fine-tuning these pre-trained models, the features extracted from the last convolutional layers (before the fully connected layers) are fed into machine learning classifiers for further analysis.

C. Feature Selection and Dimensionality Reduction

Once the deep learning models extract features, the next step involves selecting the most relevant features for classification. Given that CNNs often produce high dimensional feature vectors, dimensionality reduction techniques like Principal Component Analysis (PCA) or t Distributed Stochastic Neighbor Embedding (t-SNE) are employed. This reduces the computational load and ensures that the classifiers focus on the most significant features, improving both accuracy and processing speed.

D. Classification Via Machine Learning Algorithms

These reduced feature sets from the operational aspect are utilized to train the machine learning classifiers. The proposed system utilizes two classifiers - the Random Forest and Support Vector Machines (SVM).

- Random Forest: The Random Forest is an ensemble learning method that constructs multiple decision trees during training, with the mode from all of these trees classifying individual test trees. The advantage of Random Forest is its power to handle linear or non-linear data. By employing Random Forest, one can handle pulmonary fibrosis patterns, which can range in nature from shape to size to texture in different CT images.
- SVM (Support Vector Machines): SVMs are excellent classifiers when dealing with high-dimensional data. SVM is great at separating large data that are not linearly separable. The SVM fits the input features into higher dimensions, and then it hunts down the best hyperplane on which to classify data in fibrosis and nonfibrosis patterns. In this study, non-linear classification used the radial basis function (RBF) kernel.

Apart from the above explanation, it must be noted in brief that both Random Forest and SVM have their strengths. Random Forest is effective on supporting complex data structures, while SVMs are remarkable for high-dimensional data.

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E. Model Evaluation Metrics

To assess the performance of the proposed system, several evaluation metrics are used:

- Accuracy: This measures the number of right classifications for the images over the total number of images.
- Precision: This measures the number of true positive classifications (appropriately marked fibrosis) over all positive classifications (correct as well as mistaken ones).
- Recall: This measures the number of true positive classifications (true fibrosis) in all population cases of the real positives (real fibrotic cases).
- F1 score: This gives the harmonic mean of the precision and recall that gives a symmetrical evaluation to the performance of the model.

These metrics will be calculated for each classifier, and the results are compared to identify which combination of the deep learning feature extractor and the machine learning classifier performs the best.

F. Integration with Flask-Based Web Application

Final component of the proposed system is an web based applications that enables easy and real-time access for medical professionals. Flask, a lightweight Python web framework, is used to create the web interface. The integration process involves:

- Model Deployment: The trained deep learning models (InceptionV3, VGG19, and MobileNetV2) and machine learning classifiers (Random Forest and SVM) are saved and deployed within the Flask application.
- User Interface: The Flask web interface provides a simple interface where medical professionals can upload CT images of the lungs. Upon submission, the images are preprocessed, and features are extracted using the trained deep learning models.
- Real-Time Predictions: After feature extraction, the machine learning classifiers (Random Forest or SVM) predict whether the image shows signs of Pulmonary Fibrosis. The results, including confidence scores, are displayed in real-time on the web interface.
- Backend Processing: The web application handles image uploads, preprocessing, model inference, and returns predictions within a few seconds, ensuring that the system is suitable for real-time medical diagnostics.

IV. RESULT ANALYSIS

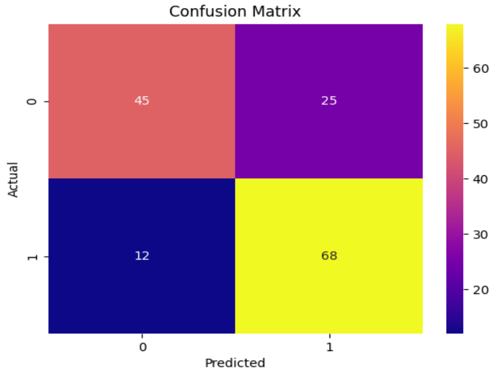

Figure 2. Confusion matrix of model1-(InceptionV3 and Random Forest)

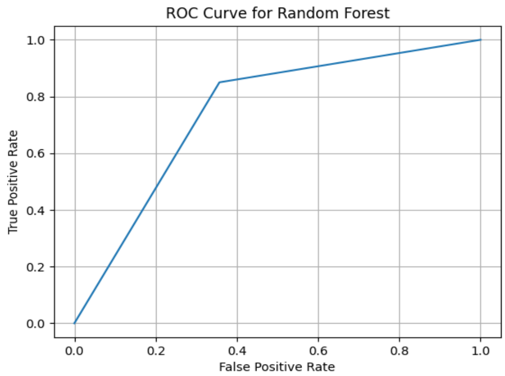

Figure 3. ROC of model1 (InceptionV3 and Random Forest)

Random Forest Classifier in fig:2 & 3 outcomes of yours show the effectiveness of the model in identifying two classes (0, 1) in the dataset with state 1 being likely related to Pulmonary Fibrosis or other classifications in your system. Here's an explanation of the key metrics and what they reveal about the Inception-based feature extraction when combined with Random Forest for classification:

Accuracy is the degree to which the tools were able to classify the right instance out of those present in the dataset. Specifically, using the Inception model features, the Random Forest Classifier achieved an accuracy of approximately 75.33% of test-set classification.

This is acceptable performance but it shows that there could be optimization in a way using a different model, over a different set of data or techniques like data augmentation.

Class 0 Performance (support = 70)

- Precision (0.79): That is 3 out of all the instances that were classified under class 0 were precise, a precision of 79%. This indicates that the model is actually quite capable of doing a reasonable job in not flagging many false positives for this class.
- Recall (0.64): As for class 0 instances, the model accurately classified 64 per cent of the actual class 0

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samples. Fewer samples recalled to class 0 means the model is failing to predict some positive samples (the false-negative problem).

- F1-Score (0.71): Precision and recall are combined into a single value by F1 score. While the score of 0.71 suggests fair performance for class 0 the model seems to be also predicting some instances of class 0 when they should not be.

Support 80 = Class 1 Performance

- Precision (0.73): If we consider class 1, it turns out that the model accurately classified actually 73 percent of the instances.
- Recall (0.85): Class 1: 85% of actual class 1 instances were retrieved clearly showing improved identification of class 1 over class 0.
- F1-Score (0.79): As for class 1, it also reaches 0.79 of F1, meaning that in fact we achieved better results than for class 0 because of increasing both precision and recall.

Macro and Weighted Averages

- Macro Avg (0.76): This is a three-point mean of precision, recall, and F1 for the two classes which are computed without weighting. What it means is that the model is probable to perform fairly uniformly across classes but marginally in favor of class 1.
- Weighted Avg (0.76): This has regard to the number of instances that support each class and is generally a better measure of the performance of the model. These equal tendencies of both weighted and macro averages suggest that class imbalance is not a matter of concern here.

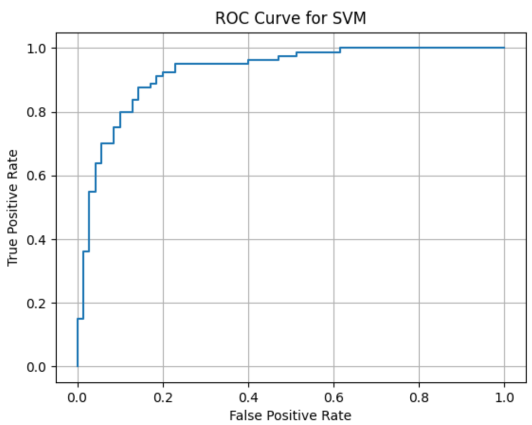

Figure 4. ROC of model2 (VGG16 and Random Forest)

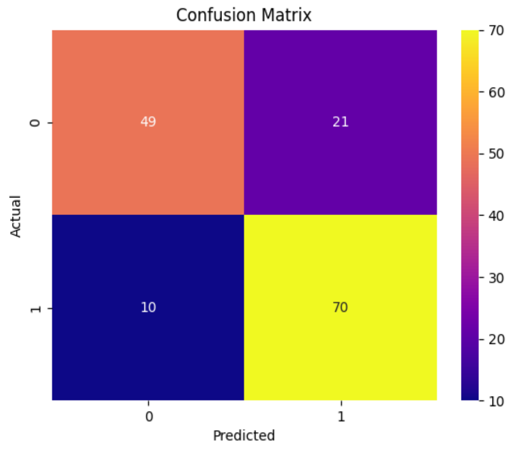

Figure 5. Confusion matrix of model2-(VGG16 and Random Forest)

The final work of the SVM classifier in fig:5 and 6 with the accuracy of 86.67% shows that the model is highly effective when using VGG16 for extracting features. Let's break down the results and how VGG16's architecture contributes to the performance:

The measurement of accuracy shows that the model identified slightly over 87 percent of the existent instances in the test data. Compared to the Random Forest classifier performance here, there is a slight increase and this we can attribute to the fact that SVM is capable of creating more complex decision boundaries.

Class 0 Performance When support = 70

- Precision (0.89): Among all the instances that the system classified as class 0, 89% were of the same classification. This implies that the model has a low tendency of misclassifying instances from class 0, which make it capture most instances from this class appropriately.
- Recall (0.81): As for the models' accuracy in defining class 0, it was as follows: the model correctly determined 81% of actual cases. Nevertheless, this recall is still rather elevated which hints at the fact that the required model might be missing up to 19% of class 0 instances or false negatives.
- F1-Score (0.85): The F1-score combines both recall and precision and shows encouraging results: the accuracy of identifying class 0 is satisfactory while ensuring the minimum number of mistakes.

First Class Performance (support = 80)

- Precision (0.85): Precision for class 1 shows that, 85% of instances that were predicted as belonging to this class were indeed accurate. This slightly lower precision than for class 0 means that perhaps, the model has developed more instances of false positives for class 1.

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- Recall (0.91): The high 91% of actual class 1 instances was accurately extracted by the model proving its good performance in terms of class 1 false negatives.
- F1-Score (0.88): This balanced metric indicates that the classifier is nearly perfect on class 1 and it is pretty good on recall and precision tradeoff.

Macro and Weighted Averages

- Macro Avg (0.87): This is the average of the simplest case – unweighted – precision, recall and the F1-score overall two classes. The scores of two classes are relatively close, which means the proposed model is satisfactory on the whole.
- Weighted Avg (0.87): This average represents relative strengths of the classes; the number of instances supporting or backing each class demonstrated that the classifier is sound and performs well across the board.

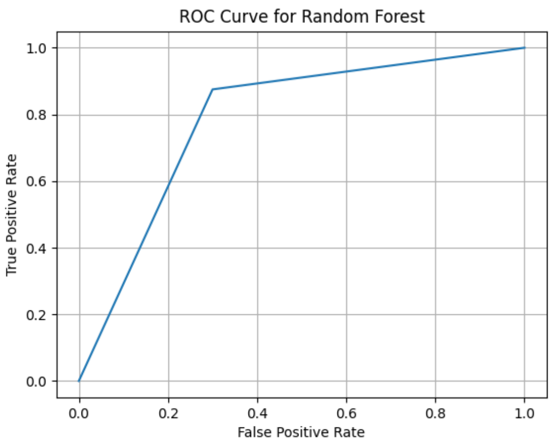

Figure 6. ROC of model3 (MobileNetV2 and Random Forest)

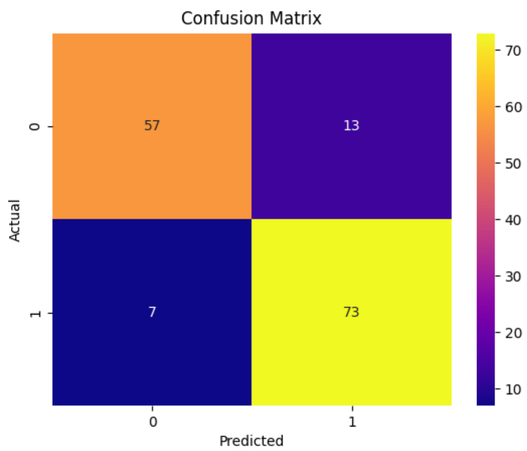

Figure 7. Confusion Matrix of model3 (MobileNetV2 and Random Forest)

The outcome of the Random Forest Classifier with accuracy of 79.33% in fig 6 & 7 indicates good performance of the model when MobileNetV2 is used for feature extraction. Here's an explanation of how MobileNetV2 contributes to these results, along with an analysis of the key performance metrics:

This means that the Random Forest Classifier performance was 79.33% accurate in classifying the entire range of instances. This is even better than in earlier cases when working with other models, which testifies to the fact that MobileNetV2 in the capacity of a feature extractor is efficient if used in this scenario.

Chap 0 Performance (support = 70)

- Precision (0.83): In class 0, the classifier got 83% of the instances right which had been tagged as class 0. This means that the classifier does a reasonably good job in recognizing class 0 even though an 83 percent precision indicate that there were some false positives.
- Recall (0.70): The model was able to predict class 0 with good precision, where 70% of the actual class 0 samples were succeeded to be predicted by the model. This lower recall shows that the model fails to rescue some instances from class 0, therefore resulting in false negatives.
- F1-Score (0.76): In terms of precision and recall the F1-score shows that class 0 on the whole is correctly classified albeit at a lower recall value.

Support = 80 Class 1 Performance

- Precision (0.77): In the class 1, the accuracy to the predictions was at 77 percent. The specificity of the results points to the fact that while the main idea of the model is fairly successful, it is only hinting at false positives for class 1.
- Recall (0.88): In the aspects of recall, the model has 88% of recall rate to actual class 1 instance. Such a high recall also points to the strong ability of the classifier of identifying class 1 and preventing a large number of false negatives.
- F1-Score (0.82): This score is quite fine because it will make a balance between precision and recall for class 1 which is quite important.

Figure 8. Webframework prediction

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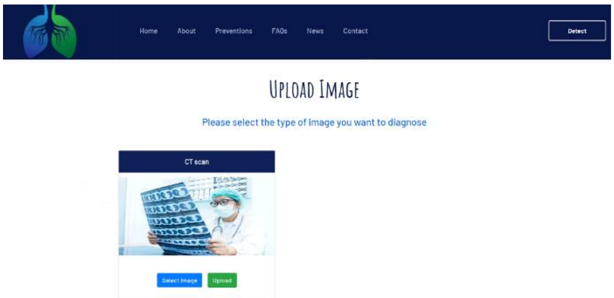

Figure 9. Webframework prediction

V. CONCLUSION

The new automatic system for recognizing Pulmonary Fibrosis from CT images should be seen as a major improvement to the diagnostic process which otherwise typically involves time-consuming and exhaustive interpretation of images by radiologists. Thanks to the selection of the InceptionV3, VGG19, and MobileNetV2 models for feature extraction, the identified pathology patterns are complex. The advantage of using the Random Forest and SVM classification models ensures that results are accurate and closer to actuality. The evaluation measures such as accuracy, precision, recall and F1 score − prove that the proposed system works fairly well to identify Pulmonary Fibrosis that makes it an effective diagnostic tool. Including this system into a Flask-based web application is achieved in such a way that it provides easy interaction with the system: simply upload the CT images and get the result from the medical specialists. It does this through expanding the access to timely decision making, early interventional activities and positive patient outcomes; thereby creating it an important tool in clinical contexts. In all, this hybrid approach appears very promising to alter the detection and intervention of Pulmonary Fibrosis – the design is flexible and scalable to accommodate more patient cohorts, and the framework can be utilized for other pulmonary diseases as well.

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