Image Super-resolution based classification of COVID-19 patients using CNN-SVM.

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Abstract: ***The first case of the Coronavirus Disease (COVID-19) was registered in December 2019 in Wuhan, China. This extremely contagious disease spread worldwide in a very short time, thus resulting in a global pandemic. To curb the spread of COVID-19, it is important to detect the virus in an infected person at the earliest. In this paper, a downright study of Multimodal Convolutional Neural Networks (m-CNN) and Support Vector Machines (SVM) will be presented for the classification of patients infected with the virus using X-ray and Computerized Tomography (CT) images. Using Transfer learning, features are extracted from the images using the fully connected m-CNN model and fed into the SVM for coronavirus classification.***

Keywords: ***Coronavirus, COVID-19, m-CNN, SVM, image-based diagnosis, Computerized Tomography, Transfer Learning.***

I. INTRODUCTION

The COVID-19 is an ongoing pandemic whose origins trace back to Wuhan. In December 2019, a virus similar to the SARS coronavirus emerged in Wuhan, China. This deadly and contagious virus was later renamed to SARS-CoV-2. Extensive research and studies conclude that this family of coronaviruses generally infect bats and pangolins in Asia. A little over 4 months from the first reported case of COVID-19, the World Health Organization (WHO), on 11th March 2020, announced the pandemic. Over 2020, this virus has infected 109 million people worldwide resulting in over 2.4 million deaths. The mortality rate of this virus is approximately 3.4%.

Virus	Year	Mortality Rate
SARS	2002	10%
MERS	2013	34%
SARS-CoV-2	2019	3.4%

Table 0 : Mortality Rates Comparison

The incubation period of COVID-19, which is the time between exposure to the virus and symptom onset, is on average 5-6 days, but can be as long as 14 days. In many instances, the infected people are asymptomatic. One of the vital reasons for the need to use intelligent systems for diagnosing COVID-19 is the high transmission rate of this disease among the people of a community. The time taken to generate the test result is comparatively greater than the time required to transmit this virus from one person to another. In such cases, X-ray images or CT scans can provide a faster and a convenient way to test the suspected individuals.

This study is intended for the same. It is targeted towards the employment of intelligent AI systems that can assist in the early detection of COVID-19 using chest X-ray images. These systems will use Convolutional Neural Networks (CNN) for feature extraction and a Support Vector Machine (SVM) for disease classification.

II. LITERATURE REVIEW

<table>
<tr><th>Papers</th><th>DataSets</th><th>Images</th><th>Classes</th><th>Techniques & Performances(%)</th></tr>
<tr><td>[1]</td><td>Not mentioned</td><td>Not mentioned</td><td>2

COVID-19(+)
COVID-19(-)</td><td><table><tr><th>Model</th><th>ACC</th><th>SEN</th><th>SPE</th></tr><tr><td>MODE based CNN</td><td>98</td><td>98.2</td><td>92.2</td></tr></table></td></tr>
<tr><td>[2]</td><td>[21], [22], [23]</td><td>341 COVID-19(+)
2800 Normal
1493 Viral Pneumonia
2772 Bacterial Pneumonia</td><td>4

COVID-19(+)
Normal
Viral pneumonia
Bacterial Pneumonia</td><td><table><tr><th>Model</th><th>ACC</th><th>REC</th><th>SPE</th><th>F1</th></tr><tr><td>ResNet50</td><td>96.1</td><td>91.8</td><td>96.6</td><td>83.5</td></tr><tr><td>ResNet101</td><td>96.1</td><td>78.3</td><td>98.2</td><td>81.2</td></tr><tr><td>ResNet152</td><td>93.9</td><td>65.4</td><td>97.3</td><td>69.8</td></tr><tr><td>InceptionV3</td><td>95.4</td><td>90.6</td><td>96.0</td><td>81.1</td></tr><tr><td>Inception-ResNet</td><td>94.2</td><td>83.5</td><td>95.4</td><td>74.8</td></tr></table></td></tr>
<tr><td>[3]</td><td>[21]</td><td>341 COVID-19(+)
310 Normal
310 Pneumonia</td><td>3

COVID-19(+)
Normal
Pneumonia classes</td><td><table><tr><th>Model</th><th>ACC</th><th>SEN</th><th>SPE</th></tr><tr><td>AOTCNeT-Softmax</td><td>99.24</td><td>99.24</td><td>99.62</td></tr><tr><td>SVM</td><td>98.60</td><td>98.60</td><td>99.30</td></tr><tr><td>RF</td><td>99.46</td><td>99.46</td><td>99.73</td></tr><tr><td>KNN</td><td>99.46</td><td>99.46</td><td>99.73</td></tr><tr><td>MobileNet-KNN</td><td>99.46</td><td>99.46</td><td>99.73</td></tr><tr><td>ShuffleNet-KNN</td><td>99.35</td><td>99.35</td><td>99.68</td></tr></table></td></tr>
<tr><td>[4]</td><td>[21]</td><td>150 COVID19(+)
150 Normal</td><td>2

COVID-19(+)
COVID-19(-)</td><td><table><tr><th>Model</th><th>ACC</th><th>REC</th><th>SPE</th><th>F1</th></tr><tr><td>CNN-Adam</td><td>94.6</td><td>93.5</td><td>94.5</td><td>90.7</td></tr><tr><td>CNN-RMSprop</td><td>88.9</td><td>85.9</td><td>88.9</td><td>86.6</td></tr><tr><td>CNN-SGD</td><td>88.4</td><td>88.7</td><td>88.5</td><td>83.0</td></tr></table></td></tr>
<tr><td>[5]</td><td>[21], [22]</td><td>284 COVID-19(+)
310 Normal
330 Pneumonia Bacterial
327 Pneumonia Viral</td><td>4

COVID-19(+)
Normal
Viral pneumonia
Bacterial Pneumonia</td><td><table><tr><th>Model</th><th>ACC</th><th>REC</th><th>SPE</th><th>F1</th></tr><tr><td>CORO-Net</td><td>90.21</td><td>90</td><td>95</td><td>91</td></tr></table></td></tr>
<tr><td>[6]</td><td>[27]</td><td>219 COVID-19(+)
1341 Normal
1345 Pneumonia</td><td>3

COVID-19(+)
Normal
Pneumonia classes</td><td><table><tr><th>Model</th><th>ACC</th><th>SEN</th><th>SPE</th><th>F1</th></tr><tr><td>mAlexNet</td><td>98.14</td><td>98.26</td><td>99.06</td><td>98.2</td></tr><tr><td>mAlexNet + BiLSTM</td><td>98.7</td><td>98.76</td><td>99.33</td><td>98.76</td></tr></table></td></tr>
<tr><td>[9]</td><td>[25]</td><td>349 COVID-19(+)
360 Normal</td><td>2

COVID-19(+)
COVID-19(-)</td><td><table><tr><th>Model</th><th>ACC</th></tr><tr><td>GoogleNet CNN</td><td>82.14</td></tr></table></td></tr>
</table>

<table>
<tr><td>[10]</td><td>[23], [25]</td><td>136 COVID-19(+)
310 Normal
162 Pneumonia</td><td>3

COVID-19(+)
Normal
Pneumonia classes</td><td>
<table>
<tr><th>Model</th><th>ACC</th><th>REC</th><th>SPE</th><th>F1</th></tr>
<tr><td>Improved ResNet</td><td>96.30</td><td>96</td><td>98</td><td>96</td></tr>
<tr><td>ResNet 50</td><td>92.59</td><td>92.5</td><td>94</td><td>92</td></tr>
<tr><td>AlexNet</td><td>88.89</td><td>88.2</td><td>95</td><td>86.5</td></tr>
<tr><td>GoogleNet</td><td>90.74</td><td>92.5</td><td>96.1</td><td>90.12</td></tr>
<tr><td>VGG-16</td><td>91.66</td><td>96.49</td><td>92.2</td><td>91.5</td></tr>
</table></td></tr>
<tr><td>[11],
[12]</td><td>[21], [27]</td><td>125 COVID-19(+)
500 Normal
500 Pneumonia</td><td>3

COVID-19(+)
Normal
Pneumonia classes</td><td>
<table>
<tr><th>Model</th><th>ACC</th><th>F1</th></tr>
<tr><td>COVID-Net</td><td>92.4</td><td>90</td></tr>
<tr><td>Bayes-SqueezeNet</td><td>98.3</td><td>98.3</td></tr>
<tr><td>VGG-19</td><td>93.48</td><td>-</td></tr>
<tr><td>MobileNet-V2</td><td>94.72</td><td>-</td></tr>
<tr><td>ResNet 50+SVM</td><td>-</td><td>95.52</td></tr>
<tr><td>DarkCOVIDNet</td><td>87.02</td><td>87.37</td></tr>
<tr><td>CORO NET</td><td>95</td><td>95.6</td></tr>
<tr><td>VGG-16</td><td>99.57</td><td>99.36</td></tr>
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<tr><td>[14]</td><td>[28]</td><td>430 COVID-19(+)
550 Normal</td><td>2

COVID-19(+)
COVID-19(-)</td><td>
<table>
<tr><th>Model</th><th>ACC</th><th>REC</th><th>F1</th></tr>
<tr><td>MLP</td><td>0.9400</td><td>0.8715</td><td>0.9268</td></tr>
<tr><td>CNN</td><td>0.9760</td><td>0.9724</td><td>0.9724</td></tr>
<tr><td>SVM</td><td>0.9920</td><td>1.000</td><td>0.990</td></tr>
<tr><td>NB</td><td>0.9400</td><td>0.9541</td><td>0.9327</td></tr>
<tr><td>AdaBoost</td><td>0.9600</td><td>0.9633</td><td>0.9545</td></tr>
<tr><td>GBDT</td><td>0.9520</td><td>0.9816</td><td>0.9469</td></tr>
</table></td></tr>
<tr><td>[15]</td><td>[21], [29]</td><td>912 images</td><td>2

COVID-19 (+ve)
COVID-19 (-ve)</td><td>
<table>
<tr><th>Model</th><th>ACC</th><th>SEN</th><th>SPE</th></tr>
<tr><td>CNN-Softmax</td><td>95.2</td><td>93.3</td><td>100</td></tr>
<tr><td>CNN-SVM</td><td>90.5</td><td>86.7</td><td>100</td></tr>
<tr><td>CNN-RF</td><td>81</td><td>76.5</td><td>100</td></tr>
</table></td></tr>
<tr><td>[16]</td><td>No access link (only mentioned GitHub)</td><td>No access link (only mentioned GitHub)</td><td>2

COVID-19 (+ve)
COVID-19 (-ve)</td><td>
<table>
<tr><th>Model</th><th>ACC</th></tr>
<tr><td>GLCN -> SVM</td><td>57.1</td></tr>
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<tr><td>[17]</td><td>Manual Data Collection through Google Forms.
(text format)</td><td>Manual Data Collection through Google Forms.
(text format)</td><td>2

COVID-19 (+ve)
COVID-19 (-ve)</td><td>
<table>
<tr><th>Model</th><th>Mean (%)</th><th>STD(%)</th></tr>
<tr><td>LR</td><td>96.667</td><td>10</td></tr>
<tr><td>SVM</td><td>97.78</td><td>6.67</td></tr>
<tr><td>DT</td><td>93.33</td><td>13.333</td></tr>
<tr><td>KNN</td><td>78.33</td><td>23.629</td></tr>
</table></td></tr>
</table>

<table>
<tr><td>[18]</td><td>[27]</td><td>1200 COVID-19 (+)
1345 Pneumonia
1341 Normal</td><td>3

COVID-19
Normal
Pneumonia classes</td><td>
<table>
<tr><th>Model</th><th>Class</th><th>ACC</th><th>REC</th><th>F1</th></tr>
<tr><td>CNN</td><td>COVID-19</td><td></td><td>99.79</td><td>99.69</td></tr>
<tr><td></td><td>Pneumonia</td><td>96.90</td><td>99.44</td><td>95.53</td></tr>
<tr><td></td><td>Normal</td><td></td><td>90.94</td><td>94.89</td></tr>
<tr><td>CNN-SVM</td><td>COVID-19</td><td></td><td>99.75</td><td>99.85</td></tr>
<tr><td></td><td>Pneumonia</td><td>99.53</td><td>99.48</td><td>99.40</td></tr>
<tr><td></td><td>Normal</td><td></td><td>99.41</td><td>99.39</td></tr>
</table>
</td></tr>
<tr><td>[19]</td><td>[21], [26]</td><td>217 COVID-19
108 Other Diseases
112 Healthy</td><td>3

COVID-19
Healthy
Other Diseases</td><td>
<table>
<tr><th>Model</th><th>ACC</th><th>F1</th><th>MCC</th></tr>
<tr><td>CNN_1</td><td>96.67</td><td>96.63</td><td>93.48</td></tr>
<tr><td>CNN_2</td><td>96.73</td><td>96.67</td><td>93.74</td></tr>
<tr><td>SVM_{Lin}</td><td>80.79</td><td>80.21</td><td>61.98</td></tr>
<tr><td>SVM_{Pol}</td><td>77.90</td><td>77.24</td><td>56.30</td></tr>
<tr><td>SVM_{RBF}</td><td>83.45</td><td>83.86</td><td>67.39</td></tr>
</table>
</td></tr>
<tr><td>[20]</td><td>[21], [25]</td><td>127 COVID-19 (+ve)
127 Pneumonia (+ve)
127 healthy</td><td>3

COVID-19
Normal
Pneumonia classes</td><td>
<table>
<tr><th>Model</th><th>SEN</th><th>FPR</th><th>F1</th></tr>
<tr><td>AlexNet</td><td>94.86</td><td>2.56</td><td>94.85</td></tr>
<tr><td>GoogleNet</td><td>91.73</td><td>4.13</td><td>91.74</td></tr>
<tr><td>InceptionV3</td><td>90.26</td><td>4.86</td><td>90.28</td></tr>
<tr><td>MobileNetV2</td><td>94.46</td><td>2.76</td><td>94.46</td></tr>
<tr><td>ResNet18</td><td>94.26</td><td>2.86</td><td>94.25</td></tr>
<tr><td>ShuffleNet</td><td>65.26</td><td>17.36</td><td>58.79</td></tr>
<tr><td>VGG16</td><td>94.20</td><td>2.90</td><td>94.20</td></tr>
</table>
</td></tr>
</table>

Table 1 : SUMMARY OF ML and DL BASED COVID-19 DIAGNOSIS IN CT IMAGES

III. METHODOLOGY

The methodology that the team has implemented consists of three **pre-trained** models, namely, **EfficientNet B3, ResNet50, and VGG16**. This methodology is slightly different from the base paper.

A. Image Preprocessing:

All the images of both the classes are resized. The images will be resized thrice. For EffNet B3, ResNet50, and VGG16, the images would be resized to 300*300, 512*512, 224*224 respectively.

B. Dataset Split :

The dataset will be split into 7:3 ratio i.e. into training and validation sets respectively.

C. Feature Extraction :

We used a pre-trained Convolutional Neural Network model that has been trained on Imagenet dataset, for key feature extraction from the dataset we provide. As you might have noticed the 3 models used were VGG16 which has 138M parameters and a depth of 23, Resnet 50 which has 25M parameters and EfficentNet B3 which has 12M parameters. After extracting features from the whole dataset individually, we split them into train and test sets and pass through different classifiers.

D. Classifier :

For this component, we have tested our features from all 3 Neural network models on SVM using Radial Basis Function (RBF) as a kernel in our classifier.

We train the model on the train set and finally test our model by passing the test set through the classifiers.

All three classifiers will provide us with 3 sets of results where each result in the set will be the probabilities of all possible class labels.

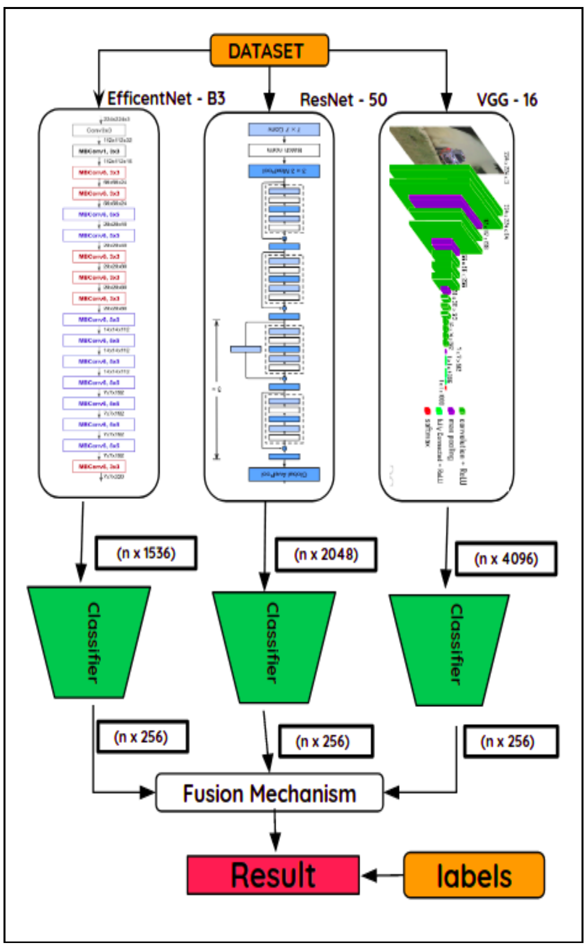
E. Fusion Mechanism :

We combine the three result sets by taking the average of the three results. The combined result set will have the probability of each class label for each test. This set would be our final result.

The final result will be a classification between 2 classes (Normal, COVID-19(+)).

Below is the aforementioned methodology in a Graphical representation

Figure 1 : Graphical Methodology.



IV. DATASET

The dataset used is the Mendeley Dataset. It contains images of two classes, namely COVID and non-COVID. There are 5500 and 4404 Non-COVID and COVID X-ray images respectively.

Class	No. of Images
Non - COVID-19	5500
COVID-19	4044

Table 3 : Dataset 2 summary

V. SOFTWARE AND HARDWARE REQUIREMENTS

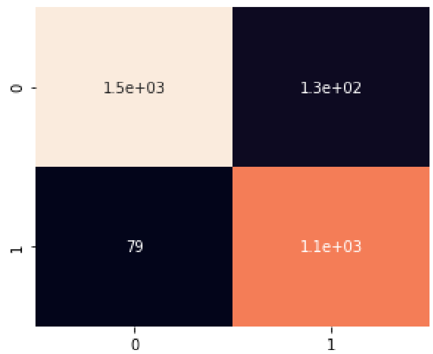
Software	Hardware
Numpy	Intel i7
Pandas	18 GB RAM(Colab)
Pytorch	NVIDIA GTX(Colab)
sklearn	
Keras	
Tensorflow	

Table 4 : Requirements

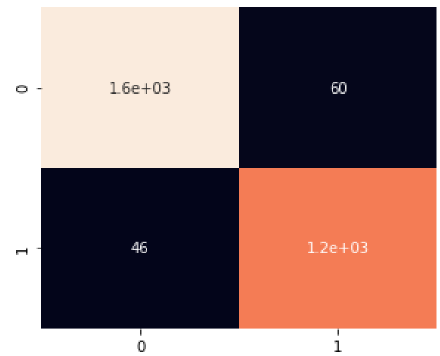
VII. RESULTS

Our initial results are obtained by testing the neural networks individually.

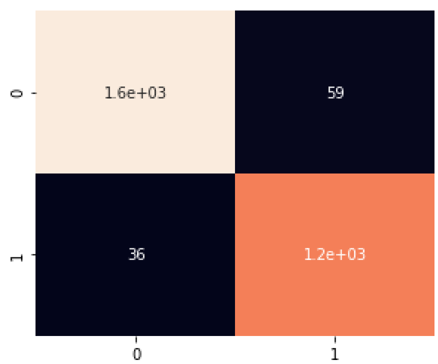
The final result is an agglomeration of all the predictions or commonly known as feature fusion. The vgg16 pre trained neural network model with svm classifier provides us with an approximate accuracy of 92.7%. Similarly, the resnet50 neural network model with SVM as the classifier yielded an approximate accuracy of 96.68% and EfficentNet-B3 Model provided an accuracy of 96.298%. The confusion matrix for the same is shown below:



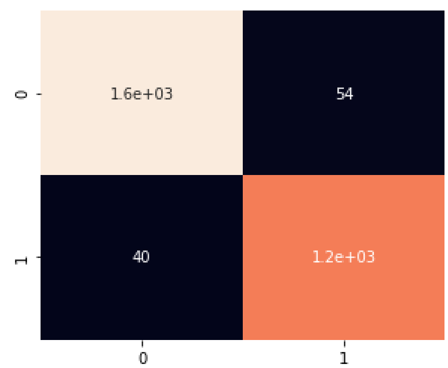
VGG16 + SVM



EfficentNetB3 + SVM



ResNet50 + SVM



Final After Voting

Model	Accuracy
VGG16 + SVM_{rbf}	92.70%
Resnet50 + SVM_{rbf}	96.68%
EfficentNet-B3 + SVM_{rbf}	96.29%
After Fusion	96.71%

Table : Accuracy Split of Models

VIII. GUI

The team has implemented this project on a GUI. The GUI was designed in Python using the PySimpleGUI module.

The PySimpleGUI window allows the user to browse through files and select an X-ray image of his/her choice for testing. After the selection of the image, the image is passed into the 3 models after pre-processing.

After classification, the result is displayed in the form of a table, as shown below:

Figure I: COVID Positive X-ray..

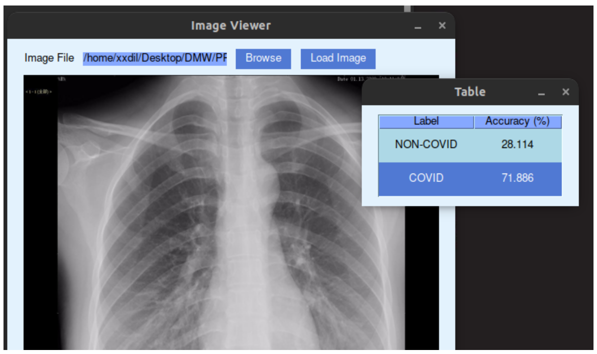
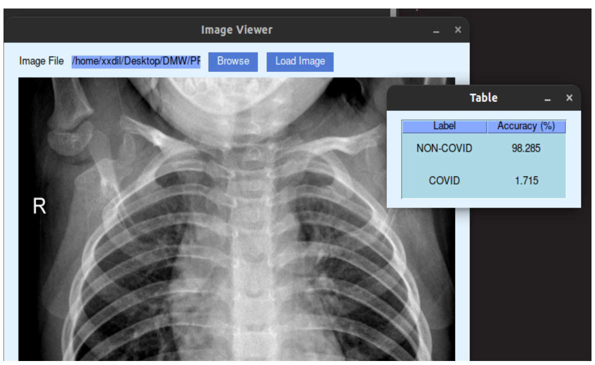


Figure II: COVID Negative X-ray.



IX. CONCLUSION

The 96.7% accuracy validates state of the art technology to accurately distinguish between covid and non covid swiftly. Since an x-ray can be taken out in a few minutes and the model can accurately identify covid individuals within a few seconds, and with the GUI developed, we could use this technology in the real world as early as possible.

X. REFERENCES

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