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# A Dual Diagnostic Measure driven pragmatic approach for nCOVID-19 Detection by Pervasive Computing

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***Abstract*— The nCOVID-19 has wreaked our normal lifestyle and has forced us to adopt the protocols under the new normal regime. The conventional diagnostic approach is expected to change in the process as well. Our research group is proposing an aid to such diagnostic approach. The group has proposed in this article the power of using two such diagnostic measures that has been the pivot for many diagnoses to the doctors. The art of using natural language processing based symptomatic measure in combination with a machine learning based approach based on medical vitals can collectively reduce the error percentage of detection. The approach proposed in this article is a first of its kind and the authors have achieved acceptable results on the accuracy front. The other reason of proposing such a technique is the way a fusion algorithm can arrive at the right results from two parallel algorithms doing the same task. Another objective of the group was to provide a valuable opinion to the doctor in form of such an architecture. The proposed architecture can be used at any point of care facilities without any requirement of escalation of the existing amenities.**

***Index Terms*— Natural Language Processing, Text Analytics, Support Vector Machine, Ensemble Learning, Body Vitals, Symptoms, COVID-19 Detection, COVID-19 Cluster Identification, Decision Fusion.**

## I. Introduction

COVID-19 has unleashed destruction and claimed a great many individuals over the globe [1]. Each Government have given open notification to keep up social distancing, wearing of masks, use of sanitizers to battle against the situation [2]. In any case, it was incredibly difficult to spread the awareness completely across the population, particularly in countries where the populace happens to be from profoundly diversified backgrounds. The major issue that every Government faced was to conduct random tests, identify the patients & isolate them from others [3]. The Government should have adequate infrastructure requirements to take care of the affected individuals with proper medical care and support. There is a growing need to be a more responsible citizen and try to practice the best preventive measures as indicated or stated to bring an end to this transmission rate. It is also important to understand the first week of symptoms since the same is very crucial given to believe that the first vaccine to hit the market is still few months away. According to various reports, studies, and continuous awareness programs, it is already known that the first week could be the key to indicate the potentiality of the virus strain [4].

The new normal trend in any commercial, housing complex, or even in hospital premises is to screen the visitors by a thermal gun and making the person answer a list of questionnaires. The process can help to identify some suspicious cases at the entry point. Our objective is to remove the human factor out of the equation and hence reduce the manual error. We have used an AI-based classification tool that we have trained on the given data set, to classify the 'COVID' patients from the 'Normal' patients based on temperature [5] & oxygen saturation percentage ($SpO_2$) [6].

Natural Language Processing (NLP) is a subdomain of computer science that mainly deals with Artificial Intelligence (AI) models and linguistics [7]. NLP is utilized for understanding natural language of people and process this contribution for different various applications utilizing a variety of algorithms [8-11]. To research millions of examples of text terms, sentences, and paragraphs written by humans, various machine learning training algorithms are used. [12].

In this paper, the authors are reporting for the first time a Natural Language Processing based classification solution that gives us an initial diagnostic understanding of the presence of COVID-19. This simple tool in combination with the AI enabled body sensor based diagnostic analysis forms the first phase of the screening process.

The pivot for our software architecture lies with a machine learning model developed on medical vitals like temperature, saturation percentage of oxygen ($SpO_2$) for predicting the presence of the virus strain. Our software architecture also takes

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additional inputs from symptomatic data like the presence of diabetes, lung disorder or fever using a text analytics enabled approach. Our software architecture then in combination predicts the presence of the virus in the affected subjects.

The significance behind such a development is multi fold. Many studies that have been conducted have witnessed that most patients tend to visit a hospital in later stage of infection, that results a poor prognosis. Hence the proposed tool is very important for early screening and isolation of the patient, that would eventually result in better prognosis of the disease. Depending on pre-existing & present medical conditions and different body vitals, we have created a model to identify a COVID affected individual and place the subject in a cluster conforming from being mild to very severe category as well. In order of criticality, six main clusters of infections were defined for our research work.

## II. Materials and Methodology

The idea of the authors is to enable all diagnostic centres inclusive of the one that have the infrastructure to conduct tests with RT-PCR, to quickly identify and isolate the affected individuals using the discussed intelligent framework. Sampling different kind of symptoms observed in the first week in combination with other body sensor readings, can help us to predict the onset of the virus infection for the subject concerned. Our AI based architecture could further help to determine the actual likelihood of COVID-19 turning dangerous and a patient undergoing hospitalization in the process.

### *A. Data Set & Preprocessing*

North Eastern Indira Gandhi Regional Institute of Health and Medical Sciences, India has provided the data both qualitative and quantitative information. The consolidated data was separated into two different data set conforming to the medical vitals and symptoms. They are further divided into training and test sets.Both the training sets had pre-defined labels whereas the test set had no pre-defined labels associated. As a pre-processing step the data was cleaned by a normalisation method to generate the missing values for the quantitative set. The authors took a different approach for the qualitative set. The missing values were completely removed from the data set. Since both, the data set were to be used separately, for training the respective models hence any mismatch in the size for the two data sets would not cause any ambiguity to the final model.

### *B. Natural Language Processing based Machine Learning Model for COVID Detection*

This step includes a text analytics algorithm based on symptoms like the presence of diabetes, respiratory distress, or history of pneumonia to correctly distinguish between COVID and healthy individuals.

COVID-19 is associated with presence of fever, cold, cough and breathlessness, abdominal pain is also one of the other symptoms. The are many having asymptotic symptoms as well. [13-15][16]. The severity of the Illness varies from mild to critical. The importance of text analytics can help us in classification of the subjects in terms of contracting the disease. Though a very initial indicative estimation is obtained in the first screening but clearly acts as an enabler to some of the confirmatory test in the immediate and following screening stages.

A novelty in our proposed methodology lies in classification from symptomatic text descriptions of patient reports and performing an initial level classification using a standard model known as Support Vector Machine (SVM) [17].

Naturally, every text data is sequential. A series of terms that may have dependencies between them is a piece of text. For understanding series of text data & to identify, we have used support vector machines and the dependencies have been extracted using the tokenized document & Bag of words concept.

There are four steps that were performed for training using the SVM model are as follows:

1. Import the Pre-processed data.
2. Then use the tokenized document & bag of words to convert the words to numeric sequences.
3. Create and train an SVM model.
4. Use trained SVM model to classify new symptomatic text data.

### *C. Comparison of the above Support Vector Machine Model with two Deep Learning Models*

LSTM network is a popular Deep Learning based model to classify text descriptions.[18]. It is a recurrent type of "RNN" neural network that works on learning long-term dependencies between the same data measures. [19]. It is important to translate a text input to an LSTM network into numerical sequences.It can be obtained by using a word encoding that maps documents to indice sequences. The four steps in Training using the LSTM network are as follows:

1. Import the pre-processed data.
2. Convert the words to numeric.
3. Create LSTM network and train them with a word embedding layer.
4. Classification is to be carried out using the newly time LSTM network.

To classify the text another model convolutional neural network or CNN in short can also be used [20].

The text data needs to be translated into images in order to identify text data using convolutions. To do this, the observations had to be padded or truncated and the documents had to be transformed word vectors of length C,to have a constant length S,. It is important to display the document as a 1-by-S-by-C picture (an image with height 1, width S, and C channels).

Using convolutional filters of different widths, the network is trained.

The following are the steps that describe the CNN Architecture:

1. Size of the input should be of 1-by-*S*-by-*C* where S is the length of the series and C is the number of features (the embedding dimension).

2. Blocks of layers containing a convolutional layer, a batch normalization layer, a ReLU layer, a dropout layer, and a max pooling layer are formed for the n-gram lengths 2, 3, 4, and 5.
3. 200 convolution filters of size 1-by-N and pooling regions of size 1-by-S are defined for each block, where N is the n-gram duration.
4. The input layer for each block is linked and concatenated using a depth concatenation layer with the outputs of the blocks.
5. A fully connected layer with the output size K, a softmax layer, and a classification layer are used to classify the outputs, where K is the number of groups.The network architecture is explained in Figure 1

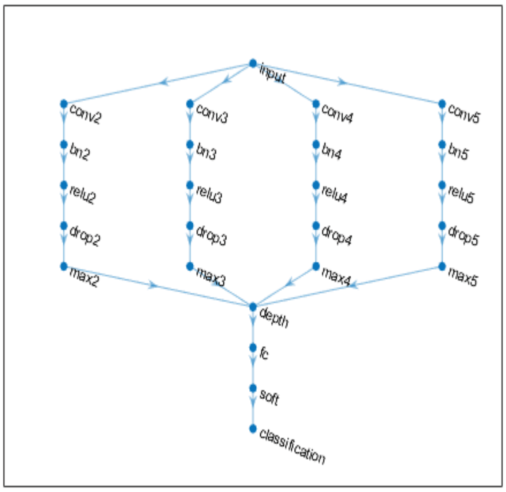


Fig.1. The Network Architecture for CNN Model

### D. Decision Fusion Algorithm

Any Decision Fusion Algorithm [21] plays a crucial role in multi-hypothesis situation and hence universally applicable in AI enabled clinical diagnostic procedures as well. The concept of multi-hypothesis will act like a valuable second opinion to the health practitioners and hence will be an enabler for any diagnostic based approach. In our case we have proposed a two-stage screening for the correct detection and isolation of the COVID subjects and their corresponding cluster depending on symptoms and vitals. To elaborate we have two sub diagnostic measures in our first Verification phase viz-a-viz sensor vitals & symptomatic analysis of subjects. This is more of a preliminary investigation cum examination as the doctors normally perform as the first level of their diagnostic procedure. Since we have created a two-step verification from different sets of Data and have drawn the respective inferences from 2 different algorithms, respectively hence we are proposing an algorithm by a "Maximization Rule" using a probabilistic measure, to correctly recognize the subject concerned in decision conflict scenarios. Our algorithm finally scans through the sets of inferences drawn from the different AI engines and finally returns the output of the class which has been Inferred the most.

The equation of our methodology is described below:
C1 represents the output class predicted by the machine learning algorithm for pathological data.
S1 represents the probability score for class C1
C2 represents the output class predicted by the deep learning model for radiographic images
S2 represents the probability score for output class C2
Let say X represents the single output given, two different output from different algorithms.
X= argmax (S1, S2); for all output classes.
The whole process is explained in Figure 2

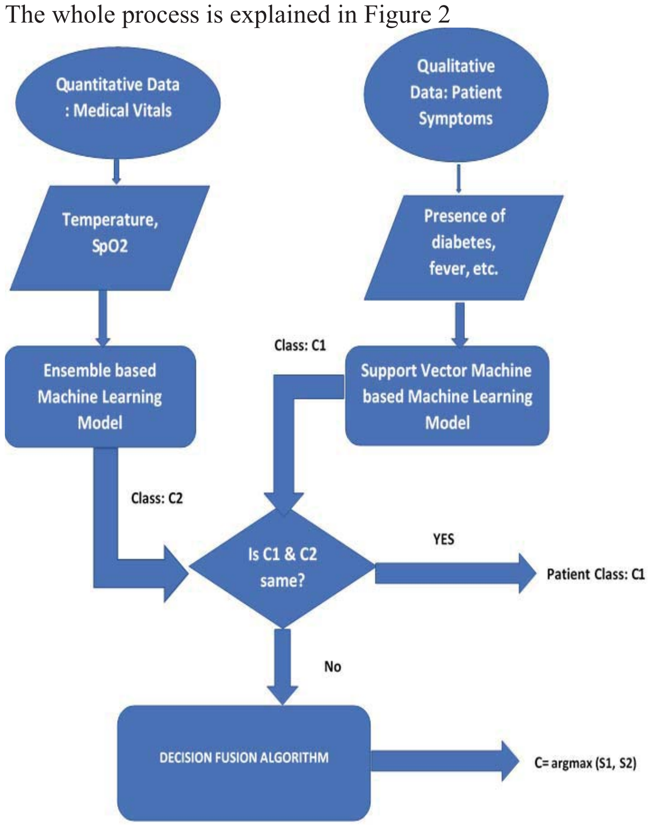


Fig. 2. Flow Chart for Decision Fusion Algorithm

### E. An NLP based Machine Learning Model for COVID CLUSTER Identification

Once a COVID-19 subject is identified, the next natural step is to group the same into one of the six clusters based on the symptoms associated with a cluster. To elaborate further, the COVID cluster identification is a methodology where the authors have tried to contribute towards segmenting the subjects into clusters depending on severity of symptoms.

As an input feed to test our support vector machine (SVM) trained model for further clustering of the COVID subjects, First, the symptomatic text information was translated into numeric sequences. These also model the connections between words by means of vector arithmetic. The support vector machine is a preferred model over other methods for Medical Diagnosis, a major reason behind our selection of the same.

The four steps that were performed for Training using the SVM model are remarkably like the Classification Approach for COVID Segmentation:

1. Identification of a COVID-19 subject.
2. Convert the words to numeric sequences using the tokenized document & bag of words. An important step for cluster segmentation based on specific symptoms.
3. Create and train an SVM model for clustering of the COVID Subjects.
4. Cluster the new symptomatic text data using the trained SVM Model.

To elaborate on our approach further, the group has tried to segment the COVID Subjects into Six Clusters.

The *Cluster-I* is termed to be the mildest form of infection, the symptoms suffered under them include Flu without Fever, cold, sore throat, blocked nose, chest pain, muscle pain, loss of smell & headache. Only a few suffer from upper respiratory tract trouble brought on by an increased viral load.

The *Cluster-II* starts getting a little more cumbersome with Flu like infection with presence of fever. The patients belonging to this category attested to having symptoms like persistent fever, loss of appetite, hoarseness in the voice which is typically a characteristic for dry cough.

The *Cluster-III* subjects suffer from more complications inclusive of Gastrointestinal Infection. Patients belonging to this cluster suffered from symptoms which impacted their digestion and gastrointestinal functioning. Even though cough was not a prominent symptom in this cluster but affected individuals suffered from nausea, loss of appetite, vomiting, diarrhea was much more commonly observed. The other less common symptoms include headache and chest pain.

The subjects segmented under *Cluster-IV* can be labelled as Severe Level-1 and the most common symptom happens to be fatigue. The symptoms observed in this cluster of infection related to energy loss, exhaustion brought on by immunity slow down. Considered to be a warning sign for severe COVID-19 patients in this category shoed symptoms like fatigue, sore throat, fever, and cough.

The *Cluster-V* can be categorized as Severe level-2 with confusion in which the affected individuals start showing neurological symptoms as well. More severe than level 1, the type of symptoms in this cluster impacted nervous functioning and is the start of the lasting impact of COVID that could have on the brain in the long run. Some of the symptoms under this category include fever, hoarseness, confusion, sore throat, chest pain, fatigue, confusion, muscle pain, were observed.

The *Cluster-VI* subjects can be labelled as Severe Level 3 with abdominal and respiratory distress. This is the most alarming and severe kind of symptoms which set in people in the first week. Experiencing symptoms like confusion, diarrhea, shortness of breath, muscle and abdominal pain, people belonging to this cluster were much more likely to undergo hospitalization, require ventilation and oxygen support.

## III. RESULTS AND DISCUSSIONS

The quantitative data set contained age, gender, temperature & oxygen saturation as parameters for correct classification of COVID individuals were trained using the Classification Learner App in MATLAB® and the Model with the highest accuracy was automatically returned. The details of the trained model along with the different performance evaluation visualizations are provided for better understanding. The Machine Learning model parameters are given in Table 1.

The ensemble method was tested separately for Bag, Ada Boost & RUS Boost. The number of learners was tested from 10 to 500, the Learning Rate was varied as 0.001 to 1, the number of splits was tested from 1 to 560, and the number of predictors was tested from 1 to 4. The cost matrix for misclassification was fixed as default. The final model obtained is returned as given above.

The fate our model for the given data set:

TABLE I
MACHINE LEARNING MODEL PARAMETERS

| MODEL: OPTIMIZABLE ENSEMBLE | |
|---|---|
| *Learner Type* | Decision Tree |
| *Accuracy* | 81.5% |
| *Total Misclassification Cost* | 104 |
| *Prediction Speed* | ~790 observations/sec |
| *Training Time* | 312.59 sec |
| OPTIMIZED HYPERPARAMETERS | |
| *Ensemble Method* | BAG |
| *Max No of Splits* | 556 |
| *No of Learners* | 58 |
| *No of Predictor Samples* | 4 |
| OPTIMIZER OPTIONS: BAYSEAN OPTIMIZATION | |
| *Iterations* | 30 |
| *Training Time* | 300 s (True) |

The confusion matrix, Receiver Operating Characteristics (ROC) plot and Misclassification Error Plot of Machine Learning Model is given in Figure 3-5.

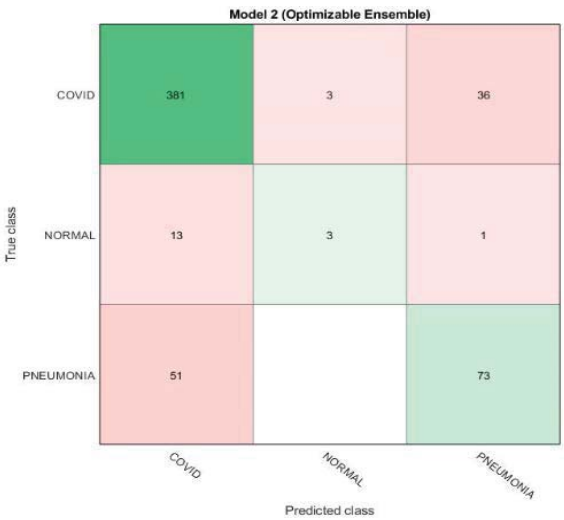


Fig. 3. Confusion Matrix of Machine Learning Model

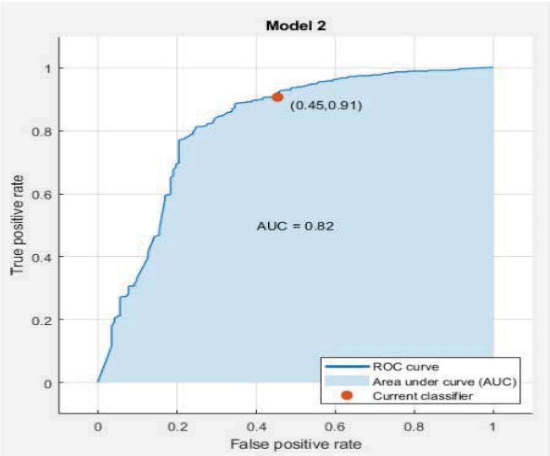


Fig. 4. Receiver Operating Characteristics Plot of Machine Learning Model

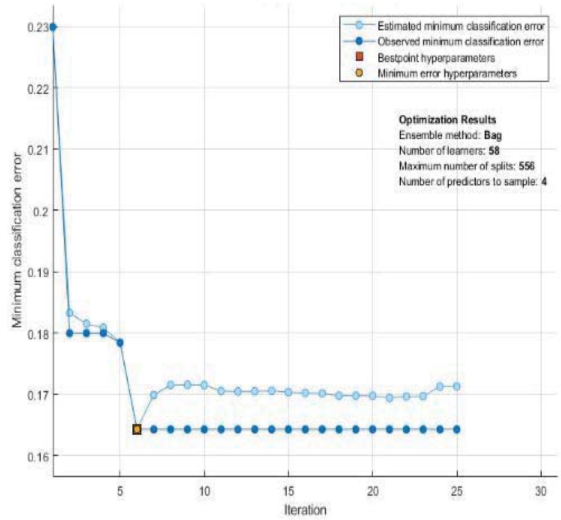


Fig. 5. Misclassification Error Plot of Machine Learning Model

Some of the important Mathematical deductions from Figure 4 are as follows:

(i) Sensitivity (COVID) ~ **90.71%**
(ii) Specificity (Normal) ~**17.65%**
(iii) Specificity (Pneumonia) ~ **58.87%**
(iv) The AUC of ROC Plot is obtained as 0.82. The Larger the area more the accuracy of the model. Hence quite indicative that the model obtained is a highly robust one.
(v) The misclassification (Figure 5) or Error Value (**~0.165**) was optimized below the acceptable limit as well.

The two main factors that play a pivotal role in selecting the correct model are sensitivity & specificity. In simple terms and as an explanation for the above observations (confusion matrix) we find that 'COVID' (target class) detected as 'COVID '(output class) define the sensitivity. It is observed that the sensitivity test for 'COVID' has a higher accuracy return. In addition to it, the false negatives in respect to the candidate being predicted as 'Normal' is also low. The other false negative conforming to the 'Pneumonia' aspect is of little importance since the same requires addressable medical measures.

The other part analogous to sensitivity is specificity. We have defined the same in two ways. One being defined by 'Normal' (target class) detected as 'Normal' (output class). We find that the sensor data are not overly specific in Nature. The 'Normal' detected as 'COVID' is important but not to a greater extent since they do not risk of spreading the disease. The number of false positives may bring the accuracy of our model down but from medical criticality, it is of low severity over the false negative aspect.

The second specific class being 'Pneumonia'. We observe that the Accuracy in terms of the same is around 59%. But none of the candidates have been misclassified as 'Normal'. Though sizeable portions have been misclassified as 'COVID' but again the individuals can go through further confirmatory examinations for a more correct inference. Since the overall accuracy of an AI-based System is built around the true positives & false negatives count hence the entire model was made to cater to the same. The precision metric which accounts for the false positives among the true positives, is reasonable.

The qualitative data was used as an input feed to test our Support Vector Machine (SVM) trained model. A comparative table to identify the superior model on the following parameters is given below in Table 2.

The machine learning model, support vector machine outperforms the two deep learning models on most performance evaluation metrics. The sensitivity metric was marginally higher for the two Deep Learning Models but for the other evaluation metrics viz-a-viz accuracy and sensitivity, the support vector machine is found superior over the other two Deep Learning Models.

The symptomatic analysis of few subjects and their respective cluster segmentation are discussed in Table 3:

TABLE 2
COMPARATIVE TABLE TO IDENTIFY SUPERIOR MODEL

| Model | Parameters | Scores in % |
|---|---|---|
| Support Vector Machine (SVM) | Sensitivity (COVID) | 97.39 |
| | Specificity (Normal) | 83.33 |
| | Specificity (Pneumonia) | 68.85 |
| | Precision | 90.56 |
| | Accuracy | 9.43 |
| Long Short-Term Memory (LSTM) | Sensitivity (COVID) | 98.44 |
| | Specificity (Normal) | 0 |
| | Specificity (Pneumonia) | 54.10 |
| | Precision | 85.91 |
| | Accuracy | 86.72 |
| Convolutional Neural Network (CNN) | Sensitivity (COVID) | 97.65 |
| | Specificity (Normal) | 0 |
| | Specificity (Pneumonia) | 53.28 |

| | |
|---|---|
| Precision | 85.62 |
| Accuracy | 85.94 |

TABLE 3
THE SYMPTOMATIC ANALYSIS OF A SAMPLE AND THEIR RESPECTIVE SEGMENTATION

| SL. NO | SYMPTOMS | ACTUAL LABELS | PREDICTED LABELS | CLUSTER |
|---|---|---|---|---|
| 1 | "Hypertension, Type 2 diabetes, Coronary Heart Disease, Lung cancer, Low-grade Fever and Fatigue, Travel History" | COVID | COVID | Cluster-III |
| 2 | " Hypertension, Type 2 Diabetes, Coronary Heart Disease, Low-grade Fever and Fatigue. Travel History." | COVID | COVID | Cluster-II |
| 3 | " Hypertension, Type 2 Diabetes, Coronary Heart Disease, Low-grade Fever and Fatigue. Travel History." | COVID | COVID | Cluster-II |
| 4 | " Fever and Non-Productive cough, Travel History, Controlled Hypertension, Fever, No Respiratory Distress" | COVID | COVID | Cluster-III |
| 5 | " High-grade Fever, Cough, and Fatigue for 1 week. " | COVID | COVID | Cluster-II |
| 6 | "Sore Throat, Dry Cough, Fatigue, and Low-grade Subjective Fever, history of Hypothyroidism, Travel History" | COVID | COVID | Cluster-III |

The symptoms described in the six clusters can give us indicative inferences as to how COVID-19 impacts different brackets of people and provides a look out for the kind of symptoms to expect. Of all patients, fever and cough were persistent in all groups which faded away after 3-4 days. Sense of smell was something which triggered, in the patients only after the 4$^{th}$ day post infection. The different analysis suggests that the difference in the severity of infection could only be observed after 4-5 days of infection. The segmentation is thus subjected to change and should only be considered after the 4-5 days.

## IV. CONCLUSION

For the first, in this paper the authors have reported a solution pipeline as discussed in a more composite and a robust manner, as it includes a two-step verification process. Our algorithm would be developed into a software as part of our future development and would hence act as an aid to the health practitioners & other medical staffs and provide a valuable second opinion in the preliminary diagnostic process. Our proposed methodology may help to accelerate the screening process and hence increase the number of isolation cases each day with efficient identification and clustering process. Our training data & validation conform to Asian origin. The results / observations conform to an improved mathematical model with a superior accuracy. We are working on an increased number of clinical validations to increase the acceptability and adaptability and for improvement of the same. The patients as observed belonging to the mild or moderate cluster are unlikely to record a symptom such as fatigue in the first week for patients in the severe or high-risk category. Some of the critical symptoms were observed on the start of day 1 itself. some of these symptoms included breathlessness, fatigue, and abdominal pain. The researchers said that the analysis pointed that people belonging to cluster 4,5 or 6 tended to older and frailer and were more likely to be overweight and have more severe pre-existing medical conditions than those with type 1,2 or 3. It was discovered that only 1.5 % people under Cluster-I, 4.4% under Cluster-II, 3.3% under Cluster-III, required breathing support, considered to be a mask of degradation of the disease. The identification of the clusters can make people realize how crucial monitoring symptoms are and provide priority care to those who might need it more than others and administer right tools to prevent a second wave in some people. The parameters and specific symptoms could also prove to be a breakthrough and help doctors determine the people at most risk. This would help taking timely decisions and save lives. To conclude, this paper thus illustrates the significance of monitoring symptoms over time to make our predictions about individual risk and predict more sophisticated and accurate outcomes. The approach adopted by us would eventually help to understand the unfolding story of this disease over time in each patient so they can get the best care.

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