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Prediction Of Long Cancer Severity With Computational Intelligence In Covid'19 Pandemic

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ABSTRACT
Coronavirus disease 2019 (COVID-19), caused by a newly found strain of the coronavirus family severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has quickly spread around the world, causing a significant public health crisis. As a result, there has been a significant reorganisation of hospital wards and clinical operations around the world to deal with the growing number of COVID-19-positive individuals who require hospitalisation and critical care assistance. Patients with underlying chronic conditions, such as cancer, are particularly concerned about this widespread reallocation of health resources.Lung cancer is a cancer that originates in the lungs. When cells in the body start to grow out of control, cancer develops. As a result, we offer a unique approach in which intracranial pictures are sent to recurrent neural networks to identify cancer stages and the patients' status is classified as safe or non-safe depending on the extent of lung cancer. Because of the rise in Covid, it is no longer safe for a cancer patient, particularly one with lung cancer, to visit the hospital frequently. As a result, when the situation is truly dire as determined by the results, the patient's family and doctor will be informed.Our proposed Random Forest Tree with Recurrent Neural Network will yield a 90% correct outcome.

Keywords: Covid, Lung Cancer, Random forest, Recurrent Neural Network

INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious illness caused by the coronavirus 2 that causes severe acute respiratory syndrome (SARS-CoV-2).. Since then, the disease has spread globally, resulting in a pandemic that is still underway. Fever, cough, headache, exhaustion, breathing problems, and loss of smell and taste are some of the symptoms of COVID-19. After being exposed to the virus, symptoms can appear anywhere from one to fourteen days later. At least one-third of those afflicted show no signs or symptoms.

Most patients (81%) have mild to moderate symptoms (up to mild pneumonia), while 14 percent have severe symptoms (dyspnea, hypoxia, or more than 50% lung involvement on imaging), and 5% have critical symptoms (respiratory failure, shock, or multiorgan dysfunction).

COVID-19 is spread through the air when droplets and minute airborne particles harbouring the virus are inhaled. Breathing them in is most dangerous when individuals are close together, but they can also be inhaled over greater distances, especially indoors. As a result, if a lung cancer patient visits the hospital frequently, he or she is more likely to contract Corona. We are exposed to a fresh strategy for avoiding the hospital environment in order to prevent this dilemma.

RANDOM FOREST

A random forest is a decision tree-based supervised machine learning technique. A random forest is a machine learning technique that can be used to address problems like regression and classification. It makes use of ensemble learning, which is an approach for solving complicated problems that involves multiple classifiers. There are several decision trees in a random forest algorithm. Bagging or bootstrap aggregation are used to train the 'forest' created by the random

forest method. Bagging is a machine learning approach that uses an ensemble meta-algorithm to increase accuracy.
Based on the decision trees' predictions, the (random forest) algorithm determines the outcome. It makes predictions by averaging or averaging the output of several trees. The precision of the result improves as the number of trees grows. The constraints of a decision tree algorithm are removed with a random forest. It improves precision by reducing overfitting of datasets. In order to diagnose patients, doctors use random forest algorithms. Patients' medical histories are examined to determine their diagnosis. To determine the proper dosage for the patients, previous medical records are reviewed.
As the name suggests, a random forest is made up of a huge number of individual decision trees that work together as an ensemble. Each tree in the random forest generates a class prediction, and the class with the most votes becomes the prediction of our model. Any of the individual constituent models will outperform a large number of reasonably uncorrelated models (trees) working as a committee.
The key is that the models have a low correlation. Uncorrelated models can provide ensemble forecasts that are more accurate than any of the individual predictions, similar to how low-correlation investments (such as stocks and bonds) join together to build a portfolio that is larger than the sum of its parts. The explanation for this amazing effect is that the trees defend one other from their individual mistakes (as long as they don't all make the same mistake).
While some trees will be incorrect, many more will be correct, allowing the trees to progress in the appropriate direction as a group. As a result, the following are the requirements for a successful random forest:
1. Our features must have some real signal in order for models based on them to outperform random guessing.
2. The individual trees' predictions (and thus errors) must be highly correlated.

RECURRENT NEURAL NETWORKS

A recurrent neural network (RNN) is an artificial neural network that uses sequential or time series input to learn. These deep learning techniques are often employed for ordinal or temporal issues like language translation, natural language processing (nlp), speech recognition, and image captioning, and are used in popular apps like Siri, voice search, and Google Translate. Recurrent neural networks, like feedforward and convolutional neural networks (CNNs), use training data to learn. They are distinguished by their "memory," which allows them to impact current input and output using knowledge from previous inputs.Recurrent neural networks' output is dependent on the prior elements in the sequence, whereas classic deep neural networks presume that inputs and outputs are independent of one another. While future events may be useful in predicting the outcome of a series, unidirectional recurrent neural networks cannot account for them in their predictions. The information in an RNN is looped back on itself. It evaluates the current input as well as what it's learnt from prior inputs before making a decision.

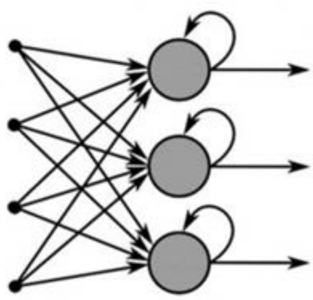

Figure 1 Recurrent Neural network

Because of its internal memory, a recurrent neural network, on the other hand, can recall such characters. It generates output, replicates it, and feeds it back into the network. Backpropagation on an unrolled RNN is referred to as BPTT. Unrolling is a visual and conceptual tool that aids in understanding what's going on in a network. Backpropagation is usually taken care of automatically when using standard programming frameworks to create a recurrent neural network, but you must understand how it works to troubleshoot difficulties that may arise throughout the development process.

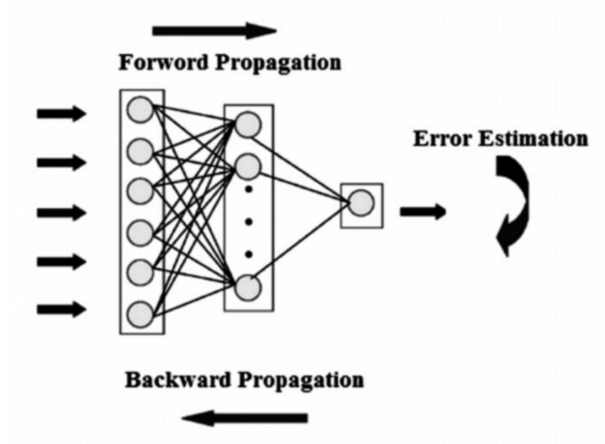

Figure 2 Propagation of Neural Network

WORKFLOWS

Data collection and pre-processing are the first steps in the suggested methodology. Using a conventional 10-fold cross-validation procedure, the chosen classifier is then trained and evaluated on the benchmark dataset. The data is analysed to determine the most effective strategy for detecting lung cancer. We used a dataset called Lung Cancer in this work, which was gathered from several IOT sensors attached to Patient.

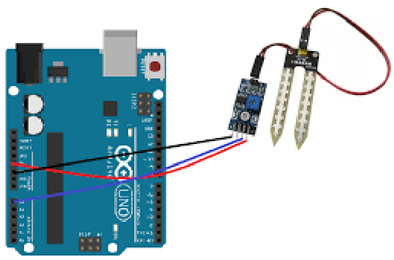

Figure3 Air bubble sensor enabled with Arduino

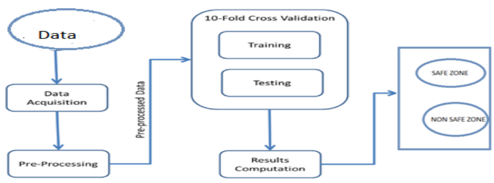

Figure 4 Workflow architecture for Classifier

Experiment workflow is universal and can be demonstrated using the stages below.
Step 1: Datasets are extracted from an online repository.
Step 2: Applying pre-processing to tidy up data.
Step 3: For training and testing, standard 10-fold cross validation is used.
Step 4: In the Random forest classifiers, compute the results for all datasets.
Step 5: Compute Random Forest results

Step 6: In the ensemble classifier, performance comparisons are made for all individual data sets, and the results of non-safe zones are sent to recurrent neural networks.

IMPLEMENTATION

The numerous air bubble sensors and pressure sensors are connected to the Arduino board shown in figure 3 and data is captured. The data is then sent to Random forest, as shown in figure 6, and the values of the random forest output are shown in figure 7. Based on the status of the patients indicated in Figure 8, the data set is trained and tested, and the results are divided into safe and non-safe zones. The cerebral images of non-safe zone patients are again sent to recurrent neural networks for further analysis, as seen in figure 10.

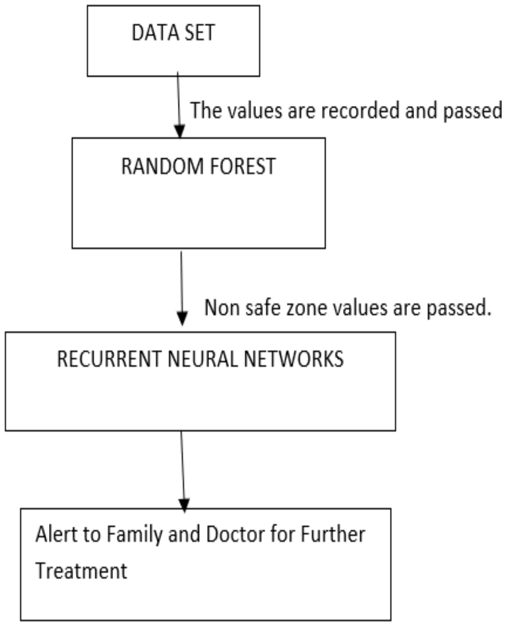

Figure 5 Block diagram of the proposed system

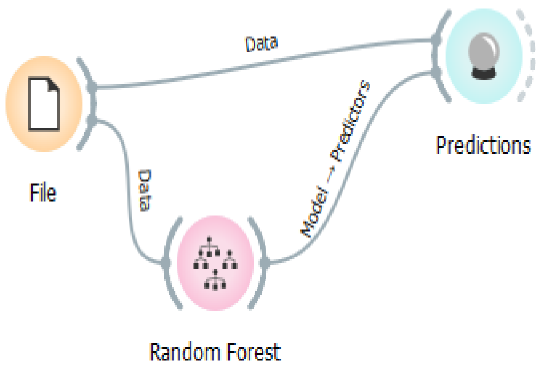

Figure 6 Random Forest Classifier connected for Prediction

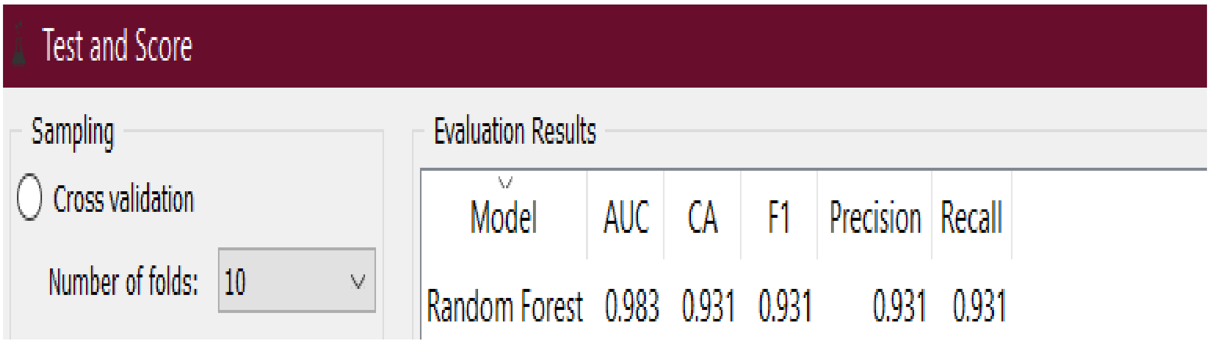

Figure 7 Random Forest Output for 10 folds

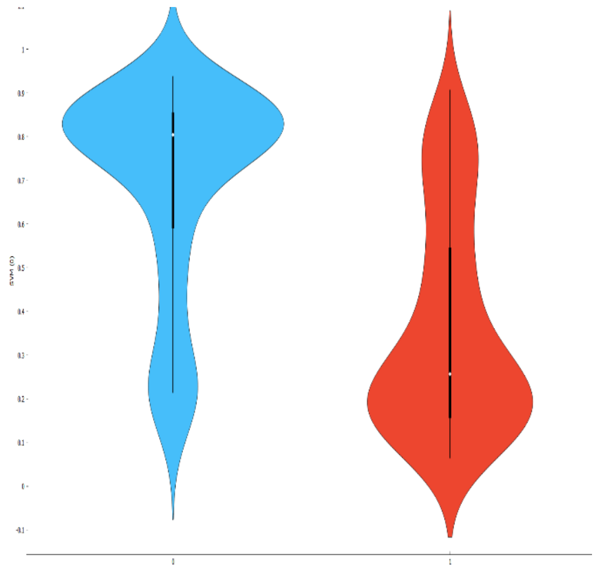

Figure 8 Random Forest Classification into Safe Zone and Non Safe Zone

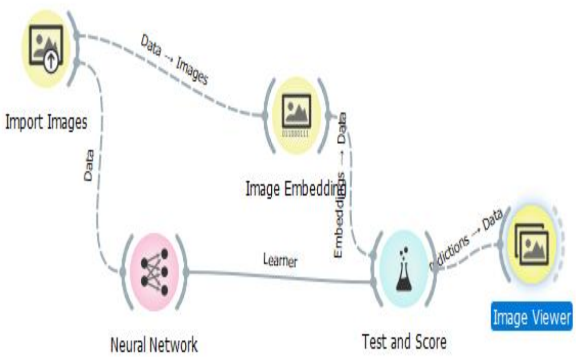

Figure 9 Neural Network implication with intracranial images

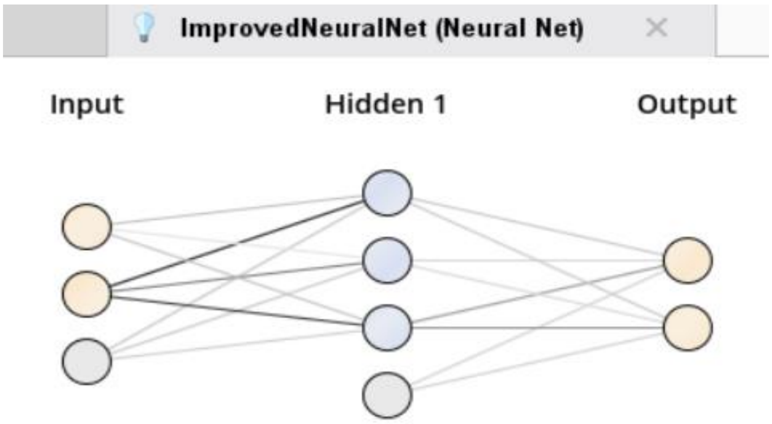

Figure 10 Neural net implication with hidden layer

RESULTS

Every time the data set value is increased from 10, 20, 40, 75, and 100, the results of Random forest followed by recurrent neural networks indicate an overall outcome of greater than 90%. Every time, when compared to all other techniques, the Random Forest produces a decent outcome.

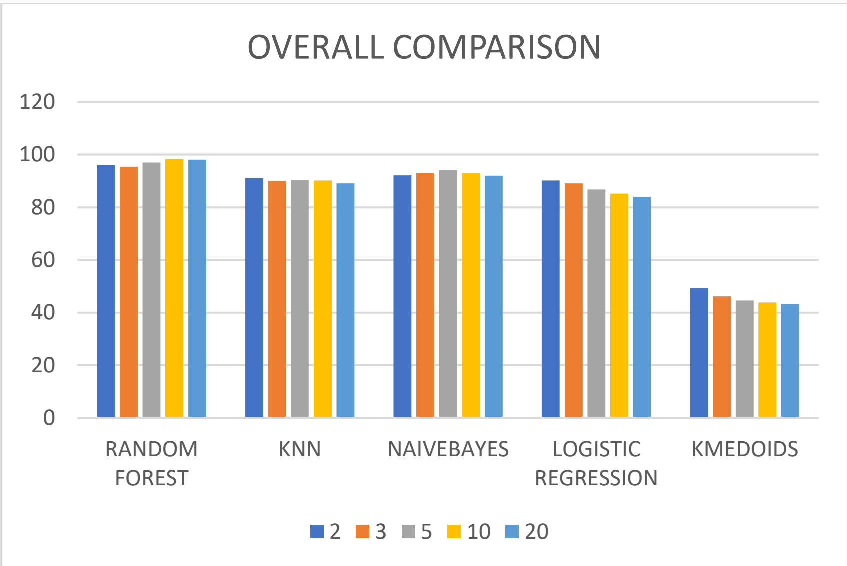

Figure 11 Overall Comparison Chart

CONCLUSION

Fedyor expressed his gratitude by saying, "It's a fantastic honour." "It's to save a life." You made a significant impact on so many people's lives." Shadow and Bone is a horror movie set in America. Leigh Bardugo is an American novelist and author. It's a fantastic quote. During a pandemic like Covid 19, admitting every patient to a hospital and examining their results is impossible. As a result of our proposed approach, many lives have been saved, and those who are well no longer need to visit the hospital or learn about new ailments. Patients who require medical attention or are in an emergency situation may be admitted to the hospital and treated there. They may also quickly adapt to this procedure and save money on MRI and CT scans because the overall cost of the components is reasonably low (about 350 rupees). When necessary, they can resume their therapies. With a 98 percent accuracy rate, we can save a patient's life.

REFERENCES

1. Mrs.G.Revathy and Dr.K.Selvakumar, “Channel assignment using tabu search in wireless mesh networks”,Wireless personal communication ISSN NO 09296212.
2. Mrs.G.Revathy and Dr.K.Selvakumar,”Increasing quality of services in wireless mesh networks”, International journal of advanced research in computer engineering and technology, vol 7, issue 3, march 2018. ISSN 22781323
3. Mrs.G.Revathy and Dr.K.Selvakumar, “Escalating quality of services with channel assignment and traffic scheduling in wireless mesh networks”, Cluster computing, Jan 2018. ISSN no 13867857.
4. Mrs G.Revathy and Dr.K.Selvakumar, “Route maintenance using tabu search and priority scheduling in wireless mesh networks”, Journal of advanced research in dynamical and control systems, vol 9,sp-6, 2017. ISSN 1943023X
5. Cabrera, J., Dionisio, A., & Solano, G. (2015, July). Lungcancer classification tool using microarray data and support vector machines. In Information, Intelligence, Systems, and Applications (IISA), 2015
6. Yu, Z., Chen, X. Z., Cui, L. H., Si, H. Z., Lu, H. J., & Liu, S. H. (2014). Prediction of lung cancer based on serum biomarkers by gene expression programming methods. Asian Pacific Journal of Cancer Prevention, 15(21), 9367-9373.
7. Wender, R., Sharpe, K. B., Westmaas, J. L., & Patel, A. V.(2016). The American Cancer Society's approach to addressing the cancer burden in the LGBT community, 3(1),15-18.
8. Li, Y., Qiu, C., Tu, J., Geng, B., Yang, J., Jiang, T., & Cui,Q. (2013). HMDD v2. 0: a database for experimentally supported human microRNA and disease associations. Nucleic acids research, 42(D1), D1070-D1074.
9. Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., & Fotiadis, D. I. (2015). Machine learning applications in cancer prognosis and prediction. Computational and structural biotechnology journal, 13, 8-17.
10. Wender, R., Sharpe, K. B., Westmaas, J. L., & Patel, A. V.(2016). The American Cancer Society's approach toaddressing the cancer burden in the LGBT community. LGBT health, 3(1), 15-18.