

# Analysis and Comparison for Innovative Prediction Technique of COVID-19 using Support Vector Machine over Neural Network algorithm with Improved Accuracy

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## ABSTRACT

**Aim:** The primary purpose of this study is to improve the accuracy of COVID-19 prediction and evaluation. **Materials and**

**Methods:** This project is based on data extracted from Kaggle's website, which is separated into two categories. According to the total sample size estimated by clinical.com, each group comprises 20 samples (N=20) for both the Support Vector Machine (SVM) and Neural Network methods, by keeping 0.05 alpha error-threshold, 95% confidence interval, enrolment ratio at 0:1, and G power at 80%. In MatLab 2021a, this entails training the data and verifying 20 validations ranging from 5 to 24.

**Results:** The SPSS Software and Independent sample T-test are used to contrast the accuracy, sensitivity, and precision rates. The Neural Network has 94.55 percent accuracy ( $P < 0.001$ ), 93.11 percent sensitivity ( $P < 0.001$ ), and 95.31 percent precision ( $P < 0.001$ ), compared to 91.25 percent accuracy ( $P < 0.001$ ), 93.93 percent sensitivity ( $P < 0.001$ ), and 86.11 percent precision ( $P < 0.001$ ) for the SVM. **Conclusion:** The Neural Network algorithm outperforms the SVM approach in terms of results.

## Keywords

Innovative COVID-19 prediction, Machine learning, Neural Network, Support vector machine, Accuracy.

## Imprint

Garudadri Venkata Sree Charan, Neelam Sanjeev Kumar. Analysis and Comparison for Innovative Prediction Technique of COVID-19 using Support Vector Machine over Neural Network algorithm with Improved Accuracy. *Cardiometry*; Special issue No. 25; December 2022; p. 904-910; DOI: 10.18137/cardiometry.2022.25.904910; Available from: <http://www.cardiometry.net/issues/no25-december-2022/covid-19-support-vector-machine>

## INTRODUCTION

COVID-19 was first discovered in 2019 and has already infected tens of thousands of people all over the world. The virus is fatal, and those who have had previous illnesses or are over 60 years old are at a higher risk of dying (Bailly et al. 2021). COVID-19 has a high prevalence, and 20% to 30% of individuals develop a moderate-to-severe version of the condition, which involves multi-organ dysfunction, protracted illness and hospitalization, and increased mortality, putting pressure on healthcare systems (Team et al. 2020). They provided a comprehensive review of the machine learning approaches and models that may be used on this expedition to aid in the fight against the COVID-19 (Shahid et al. 2021). The purpose of this research was to develop and evaluate an ML (machine learning) system for COVID-19 patient diagnosis. It was created to be used as a diagnostic instrument in hospitals when testing is restricted or unattainable (Goodman-Meza et al. 2020). The major purpose of a comparative study was to develop and validate an ML model that could predict whether a Covid-19 victim might end up dying or needed intrusive ventilatory support during their hospital stay at the time of admission. When applied at the time of hospital admission, the ML model predicts the risk of significant disease development in Covid-19 patients (Marcos et al. 2021). Our team has extensive knowledge and research experience that has translate into high quality publications (Chellapa et al. 2020; Lavanya, Kannan, and Arivalagan 2021; Raj R, D, and S 2020; Shilpa-Jain et al. 2021; S, R, and P 2021; Ramadoss, Padmanaban, and Subramanian 2022; Wu et al. 2020; Kalidoss, Umaphathy, and Rani Thirunavukkarasu 2021; Kaja et al. 2020; Antink et al. 2020; Paul et al. 2020; Malaikolundhan et al. 2020)

Around eight IEEE Explore and 87 ScienceDirect articles were found to be related to this work, which was completed in recent years and reported the developed algorithm and models for predicting and analyzing innovative COVID-19 prediction performance using ML algorithms such as Naive Bayes, Decision tree, Logistic regression. The goal of the project is to use publicly accessible data to create county-level innovative predictions for COVID-19 occurrences in the near future. The simulations showed a sensitivity of more than 71 percent and a specificity of more than

94 percent for models generated with data (Mehta et al. 2020). This study presents a comparison of ML algorithms for new COVID-19 forecasts. Among other aspects, LSTM-CNN surpassed the competition with an average mean absolute error of 3.718 percent (Dairi et al. 2021). The study's goal is to develop a simple and efficient screening tool for determining the severity of persons with COVID-19, so that they may be classified into suitable risk groups and get the proper health care (Chowdhury et al. 2021). In an alternative study, to create an improved predictor for extreme Sars-Cov-2 affected individuals. The model performed well in prediction, with an area under the curve of 0.953 (0.889-0.982). The studies proved its outstanding ability in prediction (Kang et al. 2021).

The lack of an accurate early COVID-19 diagnosis that removes human error inspired this research to predict COVID-19 at an early stage. The authors were machine learning experts who were able to perform biological research utilizing COVID-19 data and methodologies such as SVM and neural networks. The primary goal is to pinpoint COVID-19 with the maximum degree of accuracy feasible.

## MATERIALS AND METHODS

This research was carried out at the University simulation lab, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai. Based on previous study findings, the sample size was calculated using clinical.com, with an alpha error-threshold of 0.05 and an enrolment ratio of 0:1, 95 percent (An et al. 2020). Group 1 included an SVM (N=20) and a Neural Network (N=20). There are a total of 40 samples in this study.

The data samples used in the research were obtained from the Kaggle website. The data set is subjected to data reduction methods in order to obtain the absolute data required. The data should be put into MatLab 2021a to perform classification learning methods. In order to train, classification learning systems should be supplied with data. The imported data was trained twice, once for the Support vector machine with validations ranging from 5 to 24, and again for the Neural network, with validations ranging from 5 to 24. The confusion matrix should be obtained for each validation after data validation for an algorithm (Chicco, Tötsch, and Jurman 2021) which includes the TP (true positive), TN (true negative), FP (false positive), and FN (false negative) (false negative). Accuracy, Sensitivity, and Precision are

calculated with the help of these values given in Equations (1), (2), and (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

## Statistical Analysis

IBM SPSS 27.0.1 was used to compare the accuracy of the Decision tree algorithm with the Support Vector Machine algorithm. The variables like COVID samples are independent and parameters like Asthma, Headache, Diabetes and Chronic Lung disease are dependent variables. The sample T-Test was performed to find the mean accuracy, mean sensitivity, and mean precision between the two groups, and a performance comparison between the two groups is performed.

## RESULTS

Both approaches appear to give the same results, with accuracy percentages ranging from 91.25 percent to 94.55 percent, sensitivity percentages ranging from 93.93 percent to 93.11 percent, and precision percentages ranging from 86.11 percent to 95.31 percent as shown in Table 1a and Table 1b. In terms of mean accuracy, sensitivity, and precision, the neural network approach surpasses the support vector machine technique, as demonstrated in Table 2. According to the statistical research in Table 2, the neural network technique has a lower error rate than the SVM. Table 3 shows that using the independent sample T-test, there appears to be a statistically insignificant difference ( $P=0.164$  for accuracy,  $P=0.001$  for sensitivity,  $P=0.384$  for precision,  $p<0.001$ ) between the two techniques ( $P=0.164$  for accuracy,  $P=0.001$  for sensitivity,  $P=0.384$  for precision,  $p<0.001$ ). The Neural network outperformed the Support vector machine in predicting COVID-19 sickness, according to these data. The mean accuracy, sensitivity, and precision of the revolutionary COVID-19 prediction are compared to the SVM method and the Neural Network approach in Fig. 1. The Confusion Matrix of an SVM and a Neural Network is shown in Fig. 2a. and Fig. 2b. offers TP, TN, FP, and FN values, which evaluates the accuracy, sensitivity, and precision.

Table 1a

Covid-19 samples using Support Vector Machine

| Sample | Accuracy | Sensitivity | Precision |
|--------|----------|-------------|-----------|
| 1      | 0.9      | 0.93        | 0.83      |
| 2      | 0.92     | 0.94        | 0.88      |
| 3      | 0.9      | 0.94        | 0.83      |
| 4      | 0.92     | 0.94        | 0.88      |
| 5      | 0.9      | 0.91        | 0.83      |
| 6      | 0.92     | 0.93        | 0.88      |
| 7      | 0.9      | 0.92        | 0.83      |
| 8      | 0.92     | 0.94        | 0.88      |
| 9      | 0.9      | 0.94        | 0.83      |
| 10     | 0.92     | 0.93        | 0.88      |
| 11     | 0.9      | 0.92        | 0.83      |
| 12     | 0.92     | 0.94        | 0.88      |
| 13     | 0.9      | 0.93        | 0.83      |
| 14     | 0.92     | 0.92        | 0.88      |
| 15     | 0.9      | 0.93        | 0.83      |
| 16     | 0.92     | 0.93        | 0.88      |
| 17     | 0.9      | 0.94        | 0.83      |
| 18     | 0.92     | 0.94        | 0.88      |
| 19     | 0.9      | 0.94        | 0.83      |
| 20     | 0.92     | 0.9         | 0.88      |

Table 1b

Covid-19 samples using Neural Network

| Sample | Accuracy | Sensitivity | Precision |
|--------|----------|-------------|-----------|
| 1      | 0.95     | 0.94        | 0.94      |
| 2      | 0.9      | 0.88        | 0.88      |
| 3      | 0.92     | 0.89        | 0.94      |
| 4      | 0.92     | 0.89        | 0.94      |
| 5      | 0.95     | 0.94        | 0.94      |
| 6      | 0.97     | 1           | 0.94      |
| 7      | 0.95     | 0.9         | 1         |
| 8      | 0.97     | 0.94        | 1         |
| 9      | 0.95     | 0.94        | 0.94      |
| 10     | 0.97     | 0.95        | 1         |
| 11     | 0.95     | 0.94        | 0.94      |
| 12     | 0.95     | 0.94        | 0.94      |
| 13     | 0.95     | 0.94        | 0.94      |
| 14     | 0.95     | 0.88        | 0.88      |
| 15     | 0.9      | 0.89        | 0.94      |
| 16     | 0.92     | 0.89        | 0.94      |
| 17     | 0.92     | 0.94        | 0.94      |
| 18     | 0.92     | 1           | 0.94      |
| 19     | 0.95     | 0.9         | 1         |
| 20     | 0.97     | 0.94        | 1         |

Table 2

Comparison of mean accuracy, sensitivity, and precision using Support vector machine algorithm and Neural network algorithm.

| GROUP STATISTICS |                       |    |        |                |                |
|------------------|-----------------------|----|--------|----------------|----------------|
| Parameters       | Group                 | N  | Mean   | Std. Deviation | Std. ErrorMean |
| Accuracy         | Support VectorMachine | 20 | 0.9125 | 0.01282        | 0.00287        |
|                  | NeuralNetwork         | 20 | 0.9455 | 0.02228        | 0.00498        |
| Sensitivity      | Support VectorMachine | 20 | 0.9393 | 0.00189        | 0.00042        |
|                  | NeuralNetwork         | 20 | 0.9311 | 0.03460        | 0.00774        |
| Precision        | Support VectorMachine | 20 | 0.8611 | 0.02850        | 0.00637        |
|                  | NeuralNetwork         | 20 | 0.9531 | 0.03255        | 0.00728        |

## DISCUSSION

Neural Network approach offers the highest accuracy (94.55%), sensitivity (93.11%), and precision (95.31%) shown in Table 2. The meaningful difference appears to have grown slightly, despite the fact that it is not statistically significant as shown in Table 3. The easiest and most cost-effective technique for forecasting COVID-19 is the Neural Network algorithm.

The most recent works include (2020-2021) A research was conducted to discover the essential components that affect individuals utilizing analytical approaches such as univariate and multivariate regression methods, as well as logistic regression and SVM models to evaluate the p-value (John and Shaiba 2019). In a comparative study, according to the findings, the SVM model had the best accuracy (95.2%), sensitivity (87.8%), and specificity (97%) of the three algorithms (Tamal et al. 2021). Clinical prediction models are evaluated by ML and laboratory data, and accuracy, F1-score, precision, and recall are 86.66 percent, 91.89 percent, 86.75 percent, and 99.42 percent, respectively (Alakus and Turkoglu 2020). The authors developed a machine learning-based risk prioritizing method that anticipates ICU transfer within 24 hours. The RF model was trained using 10-fold cross-validation on the training set, and its prognostic ability on the testing set then was evaluated. The model tool has a 72.8 percent sensitivity and a 76.2 percent accuracy (Cheng et al. 2020). SVM and Gradient Boosted Decision tree are two of the ML approaches utilized to create the model, which has a 96.21 percent accuracy (Gao et al. 2020).

Table 3

Independent sample T-test in predicting the accuracy, sensitivity, and precision of COVID-19 using the Support vector machine algorithm and Neural Network algorithm. There appears to be an insignificant difference in both methods for Accuracy and precision with  $p > 0.05$

| Parameter   | Equal Variances | Levene's Test for Equality of Variances |       | T-test for Equality of Means |       |                            |                 |                       |                                 |
|-------------|-----------------|---|-------|------------------------------|-------|----------------------------|-----------------|-----------------------|---------------------------------|
|             |                 | F                                       | Sig.  | t                            | df    | Significance (one-Sided p) | Mean Difference | Std. Error Difference | 95% Confidence interval (Upper) |
| Accuracy    | Assumed         | 2.009                                   | 0.164 | -5.738                       | 38    | <.001                      | -.03298         | .00575                | -.02135                         |
|             | Not assumed     |   |       | -5.738                       | 30.34 | <.001                      | -.03298         | .00575                | -.02125                         |
| Sensitivity | Assumed         | 50.212                                  | 0.001 | 1.061                        | 38    | <.001                      | 0.0082          | .00775                | .02391                          |
|             | Not assumed     |   |       | 1.061                        | 19.11 | <.001                      | 0.0082          | .00775                | .02444                          |
| Precision   | Assumed         | 0.775                                   | 0.384 | -9.505                       | 38    | <.001                      | -.09196         | .00967                | -.07237                         |
|             | Not assumed     |   |       | -9.505                       | 37.37 | <.001                      | -.09196         | .00967                | -.07236                         |

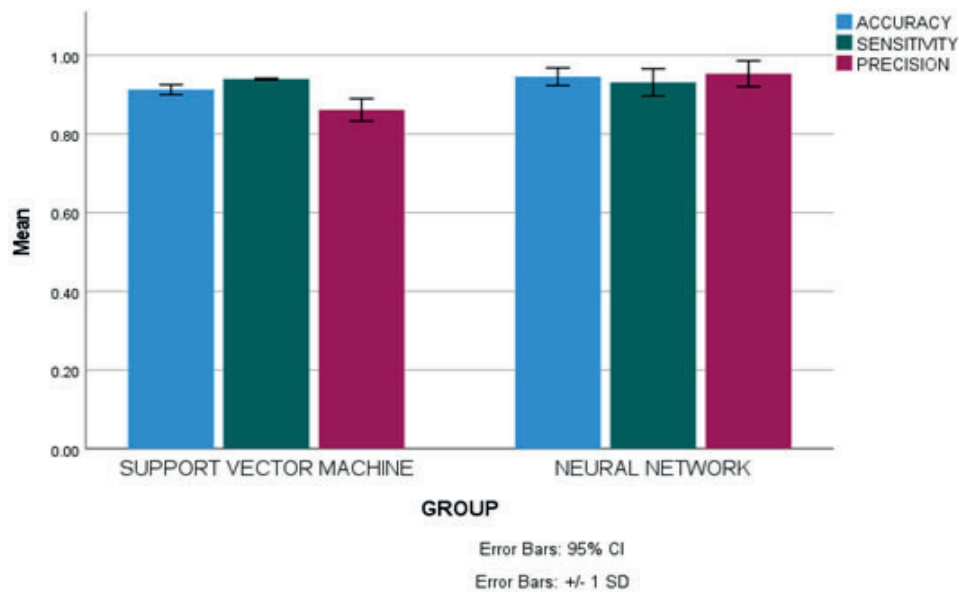


Fig. 1. Bar graph representing the comparison of mean accuracy, sensitivity, and precision of COVID-19 prediction with the Support vector machine algorithm and Neural Network algorithm. Both the techniques appear to produce the same variable results with accuracy ranging from 94.55% to 91.25%. X-axis: SVM vs Neural Network. Y-axis: mean accuracy, sensitivity, and precision detection  $\pm 1$  SD.

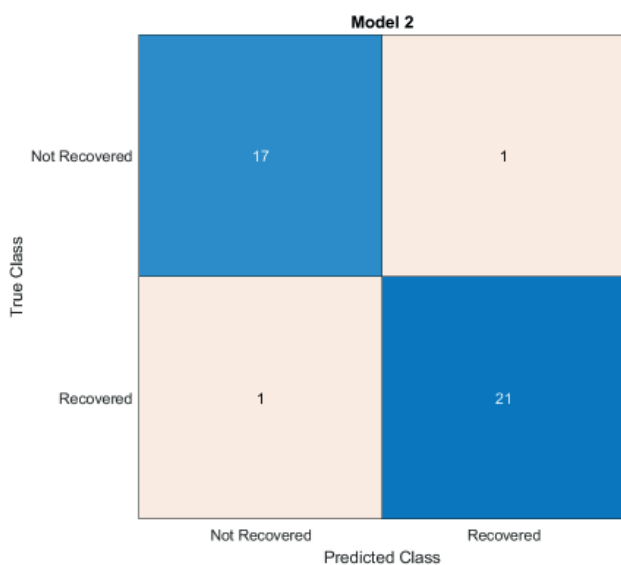


Fig. 2a. Confusion matrix for Support Vector Machine algorithm for K= 5. True Positive is found to be 17% and false positive is found to be 1%, true negative is found to be 21% and false negative is found to be 1%.

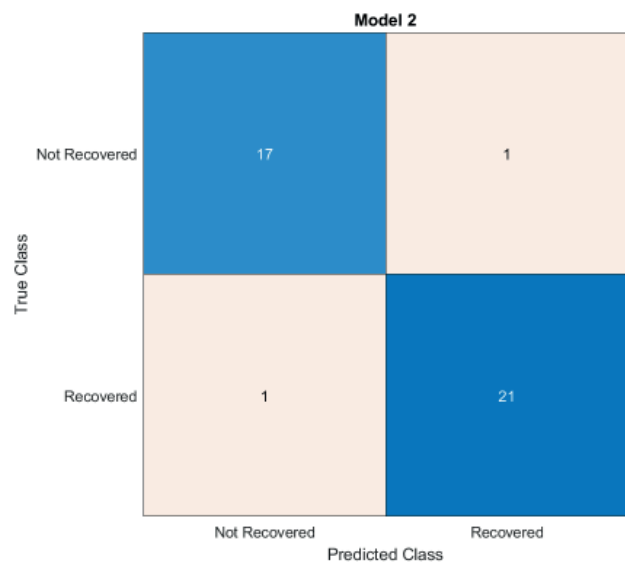


Fig. 2b. Confusion matrix for Neural Network algorithm for K= 5. True Positive is found to be 17% and false positive is found to be 1%, true negative is found to be 21% and false negative is found to be 1%.

The patient's age, gender, and whether or not he or she has a disease or illness like diabetes, pneumonia, asthma, obesity, or heart problems all have an influence on the research. This will be a significant issue because the data will not be in time series. This article examines how COVID-19 detection technology is used in the healthcare industry and how it might help with more accurate diagnoses in the future. As a consequence, this initiative has a promising future, as manual forecasting may be readily converted to automated output at a minimal cost. A larger dataset of real-time applications, in combination with additional machine learning algorithms, may yield superior results. The limitations of this research work are to increase more sample size by capitulating significant accuracy than the existing algorithm in the Innovative detection model and the future scope of this research is to ensemble the simple genetic algorithm in predicting all variants of COVID and classifying the Adaboost for feature extraction.

## CONCLUSION

In this innovative COVID-19 prediction research for the Support vector machine, the Matlab-based Neural network method (94.55 percent) generated superior results than SVM (91.25 percent). Furthermore, the algorithm's performance improved as the amount of data increased, unlike prior techniques. This model is quite efficient and has a lot of promise for predicting and analyzing COVID-19, thus it may be used in hospitals and testing facilities.

## DECLARATION

### Conflicts of Interest

No conflict of interest in this manuscript.

### Author Contributions

Author GVSC was involved in data collection, data analysis & manuscript writing. The author's learning-Based guide NSK was involved in conceptualization, data validation, and critical review of manuscripts.

### Acknowledgment

The authors would like to express their gratitude to Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (Formerly known

as Saveetha University) for successfully carrying out this work.

## Funding

We thank the following organizations for providing financial support that enabled us to complete the study.

1. Venus Electronics, Chennai
2. Saveetha University
3. Saveetha Institute of Medical And Technical Sciences
4. Saveetha School of Engineering

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