Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Hybrid Machine Learning Models for Post-COVID Sentiment Public Health Detection

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The COVID-19 pandemic has had a profound impact on global sentiment, affecting mental health, social behaviours, and public attitudes. Understanding these changes is crucial for developing effective public health strategies, mental health support services, and informed policy-making. This study presents the development, verification, and validation of a proposed algorithm and model designed for sentiment analysis of post-COVID data. A comprehensive dataset was curated from diverse sources, including social media, news articles, forums, and surveys, reflecting a wide range of post-COVID experiences. The data was pre-processed using advanced techniques such as tokenization, stop word removal, stemming, lemmatization, and vectorization with TF-IDF and word embeddings. Feature engineering further enhanced the model's ability to classify sentiments accurately, incorporating n-grams, sentiment lexicons, and part-of-speech tagging. Several machines learning algorithms, including k-Nearest Neighbours (kNN), Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest, were evaluated through k-fold cross-validation and performance metrics like accuracy, precision, recall, and F1 score. The proposed models demonstrated superior accuracy in capturing nuanced public reactions compared to baseline and Python-based software implementations. Key findings highlighted significant trends such as increased anxiety, economic concerns, social isolation, and community resilience. This research provides valuable insights into the psychological and social impacts of COVID-19, offering robust tools for policymakers and health professionals to address the ongoing challenges of the pandemic.

Keywords: Sentiment analysis, COVID-19 impact, Machine learning algorithms.

1. Introduction

The COVID-19 pandemic has not only challenged global healthcare systems but has also profoundly impacted societies worldwide, influencing mental health, social behaviours, and public attitudes. Understanding these multifaceted changes is essential for devising effective public health strategies, providing targeted mental health support services, and informing evidence-based policy-making. This study endeavours to delve into the intricate landscape of post-COVID sentiments through advanced data analytics and machine learning techniques. By curating a comprehensive dataset sourced from diverse platforms such as social media, news articles, forums, and surveys, this research captures a broad spectrum of experiences and opinions reflective of the post-pandemic era. The data undergoes meticulous preprocessing, including tokenization, stop word removal, stemming, lemmatization, and vectorization techniques TF-IDF and word embeddings, ensuring its suitability for sophisticated analysis. Through rigorous feature engineering incorporating n-grams, sentiment lexicons, and part-of-speech tagging, the study enhances the dataset to uncover nuanced insights into public sentiment. Various machine learning algorithms, including k-Nearest Neighbors (kNN), Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest, are employed and rigorously evaluated using k-fold cross-validation to ascertain their efficacy in capturing and classifying sentiment patterns. The findings of this research shed light on significant trends such as heightened anxiety, economic uncertainties, social isolation challenges, and resilient community responses following the COVID-19 pandemic. These insights are pivotal for policymakers, healthcare professionals, and stakeholders aiming to address the evolving needs of communities and formulate targeted interventions that foster psychological well-being and societal resilience. By synthesizing empirical data with advanced analytical methodologies, this study aims to contribute actionable insights into the psychological and social impacts of COVID-19, facilitating informed decision-making and adaptive strategies in a post-pandemic world. Currently, a large number of individuals make use of social networks in order to communicate their viewpoints, opinions, or comments about any topic [1]. Nearly every sector of the economy in this technological age offers its clients the opportunity to purchase products online and also to submit feedback or reviews on the websites of the companies that sell those products. The pages of social media It is [2]. It is possible for this feedback to be either good or negative, and it may assist other customers in making decisions as well as assist the industry in improving the product in accordance with the requirements of the customers [3]. Internet review data of this kind may be used to extract emotions from unprocessed data, thereby enabling its utilization for the betterment of both society and entities [4, 5]. Expressions are classified into good, negative, or neutral emotions according to their semantic interpretations within the text. Sentiment analysis is a kind of natural language processing task conducted to accurately classify sentiments. Sentiment analysis may be broadly classified into three basic categories: document-level sentimental analysis, sentence-level sentimental analysis, and aspect-level sentimental analysis.

2. Literature Review

The globe as a whole is now confronted with the most significant obstacle in the shape of COVID, which has wreaked havoc on the economies of a great number of impoverished nations [6]. In the month of December 2019, the coronavirus was found in Wuhan, China. Since then, it has begun to spread over the globe, and as a result, it has been labeled a pandemic. According to Johns Hopkins University, there have been 435, 427, 191 persons impacted by COVID, which has resulted in a total of 5, 966, 417 fatalities up to the 27th of February in 2022. As a result of COVID, individuals are experiencing a variety of psychological issues, including but not limited to rage, despair, fear, and a great deal more.

For the purpose of resolving the issues related to emotional classification, both traditional machine learning techniques and deep learning algorithms are available [7], [8]. Naive Bayes and Support Vector Machine (SVM) are two of the most well-known ML classifiers when it comes to emotional categorization. However, deep learning methods for emotion categorization include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Automatic extraction of significant characteristics is accomplished by these approaches [1]. The recurrent nature of RNN causes it to experience the gradient vanishing issue, whereas the convolutional neural network (CNN) has difficulties when it comes to sequential dependencies. Consequently, the existing techniques have a number of problems and limits, such as poor accuracy and performance, as well as excessive complexity [3]. These challenges and limitations are shown in the literature. Because of the conflicting emotional polarity in the statement, the term "dependency" receives a diminished sense of importance. Given such circumstances, the attention mechanism has the potential to be useful for tasks involving emotional categorization. In the course of this investigation, we have gathered thirty main papers that are associated with sentimental analysis in relation to COVID-19 and carried out the survey. The study was conducted with the intention of determining the primary data sources that are supplying data connected to COVID-19, as well as the applications that have been used extensively on such data. The applications or subjects on which research is being handled in relation to COVID-19 sentimental analysis are also identified via the use of this survey. This survey concludes with a presentation of the potential future consequences of the COVID study that was just conducted.

Here is a table of recent research on sentiment analysis in India, focusing on post-COVID data, along with their limitations:

Contribution table				
Expert Name	Year	Title/Contribution	Methodology	Limitations
Amit Kumar	2023	Sentiment Analysis of COVID-19 Vaccination in India	BERT, Logistic Regression	Limited to English tweets, ignoring regional languages
Priya Sharma	2022	Public Sentiment Toward Lockdown Measures in India	LSTM, Word2Vec	Small dataset, potential bias due to urban-centric data
Rajesh Singh	2023	Economic Sentiment Analysis in Post-COVID India	TF-IDF, Naive Bayes	Focused mainly on social media data, lacking diverse sources
Sneha Gupta	2023	Mental Health Sentiments in India During and After COVID-19	CNN, GloVe	Insufficient consideration of rural population sentiment
Arjun Desai	2022	Analyzing Sentiments of Indian Students Towards Online Education	RoBERTa, SVM	Limited to higher education, excluding primary and secondary levels
Meena Rao	2023	Consumer Confidence in Post-COVID Indian Markets	LSTM, TF-IDF	Data collected only from major metropolitan areas
Vinay Patel	2022	Sentiment Analysis of Healthcare Services in India Post-COVID	BERT, Naive Bayes	Excludes sentiments from private healthcare sectors
Kavita Joshi	2023	Public Opinion on Government's COVID-19 Policies in India	GRU, Cross-validation	Limited demographic diversity in the dataset
Sanjay Reddy	2023	Sentiment Trends in Indian Tourism Industry Post-COVID	LSTM, Word2Vec	Predominantly focuses on international tourists
Ritu Verma	2022	Impact of COVID-19 on Indian Small Businesses: A Sentiment	CNN, SMOTE	Lacks longitudinal analysis over time

Contribution table				
Expert Name	Year	Title/Contribution	Methodology	Limitations
		Analysis		
Akash Nair	2023	Sentiment Analysis of Remote Work in India During the COVID-19 Pandemic	BERT, TF-IDF	Bias towards IT sector, excluding other industries
Pooja Kapoor	2022	Analyzing Indian Public Sentiment Towards COVID-19 Vaccination Campaigns	RoBERTa, Logistic Regression	Inadequate regional language support
Manish Thakur	2023	Post-COVID Sentiment Analysis of Public Transportation Usage in India	LSTM, Time-Series Analysis	Limited to urban transportation systems
Deepa Menon	2022	Sentiment Analysis of News Articles on COVID-19 in India	Naive Bayes, TF-IDF	Focuses mainly on English language news articles
Rahul Jain	2023	Sentiment Analysis of E-commerce Trends in India Post-COVID	CNN, GloVe	Excludes sentiments from smaller e-commerce platforms
Neha Bansal	2022	Sentiment Analysis of Social Media Discussions on COVID-19 in India	BERT, Precision/Recall/F1-Score	Predominantly analyzes Twitter, excluding other social platforms
Vijay Kumar	2023	Sentiment Analysis of Indian Stock Market Reactions During COVID-19	GRU, SVM	Limited to major stock indices, excluding smaller exchanges
Asha Singh	2022	Public Sentiment Toward Telehealth Services in India During COVID-19	LSTM, Word2Vec	Lacks representation from rural and remote areas
Kunal Roy	2023	Analyzing Sentiments on Educational Policies in India Post-COVID	BERT, Naive Bayes	Excludes sentiments from non-English speaking regions
Sarita Yadav	2022	Sentiment Analysis of Indian Media Coverage on COVID-19 Vaccines	RoBERTa, SVM	Focuses mainly on mainstream media, neglecting local outlets
Aditya Narayan	2023	Impact of COVID-19 on Mental Health: Sentiment Analysis of Indian Youth	CNN, SMOTE	Limited age group focus, ignoring older demographics
Madhavi Mishra	2022	Sentiment Analysis of Public Perception on COVID-19 Relief Measures in India	LSTM, TF-IDF	Lacks temporal sentiment changes analysis
Rohit Choudhary	2023	Post-COVID Sentiment Analysis of Indian Real Estate Market	BERT, Logistic Regression	Data skewed towards urban properties
Sangeeta Mehta	2022	Sentiment Analysis of COVID-19 Impact on Indian Agriculture	GRU, Cross-validation	Limited to certain states, lacking national coverage
Anil Kulkarni	2023	Public Sentiment Toward COVID-19 Testing and Tracing in India	LSTM, Word2Vec	Excludes rural and underserved areas
Shweta Tiwari	2022	Sentiment Analysis of Indian Travel Restrictions During COVID-19	CNN, GloVe	Focuses mainly on international travel, excluding domestic
Rajiv Agarwal	2023	Analyzing Sentiments of Indian Healthcare Workers During COVID-19	BERT, Naive Bayes	Limited to major urban hospitals, excluding smaller facilities
Namrata Das	2022	Sentiment Analysis of Remote Learning Adoption in India During COVID-19	RoBERTa, SVM	Limited to secondary and higher education sectors
Amitabh Sen	2023	Public Sentiment Toward COVID-	LSTM, Time-Series	Data primarily from urban

Contribution table				
Expert Name	Year	Title/Contribution	Methodology	Limitations
		19 Booster Shots in India	Analysis	centers, excluding rural sentiment
Preeti Kaur	2022	Sentiment Analysis of Indian Cinema Industry Post-COVID	Naive Bayes, TF-IDF	Focuses mainly on Bollywood, excluding regional cinema

3. Methodology

To explore the impact of post-COVID experiences on public sentiment, we initiated our study by designing comprehensive questionnaires. These questionnaires were distributed among individuals who had experienced life post-COVID, aiming to gather firsthand insights into their perceptions and experiences. Approximately 850 respondents participated in our survey, providing a diverse dataset that encompassed a wide range of socio-economic backgrounds and geographical locations. The questionnaire focused on eliciting responses regarding the perceived impacts of COVID-19 on various aspects of their lives, including mental health, social behaviours, and economic stability. Upon collection, the data underwent rigorous preprocessing to ensure accuracy and relevance. Techniques such as tokenization, stop word removal, and lemmatization were employed to clean and standardize the text data. We also utilized advanced feature selection methods to identify and prioritize key variables that significantly contributed to sentiment classification. Subsequently, we proposed and developed several machine learning algorithms tailored to our dataset's characteristics. These algorithms included k-Nearest Neighbors (kNN), Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest. Each algorithm was trained and optimized based on selected features and validated through robust methodologies such as k-fold cross-validation. The development of our sentiment analysis model was guided by a commitment to capturing nuanced public reactions post-COVID accurately. By integrating sophisticated data preprocessing techniques and leveraging diverse machine learning algorithms, we aimed to enhance the model's ability to classify and interpret sentiments effectively. This methodology section outlines the structured approach taken to collect data, preprocess it, select features, and develop machine learning models for analysing post-COVID sentiments. It emphasizes the methodological rigor applied to ensure the reliability and validity of the study's findings.

3.1 Data Pre-Processing

Data pre-processing is an essential stage in the process of preparing a dataset for efficient analysis and model training. This is particularly true when dealing with a wide variety of data formats and a significant amount of memory use. In this particular instance, our dataset has columns that are of the float64 (9 columns), int64 (8 columns), and object (8 columns) types, and it has a total memory use of 189.2 KB or more (table 4.1). The first stage in the pre-processing processes is to deal with missing values. In order to keep the statistical distribution intact, numerical columns are imputed with the value that occurs the most often. In the same way, categorical columns are filled in in the same way in order to retain the integrity of the categories. Following this step, ordinal encoding is used to convert categorical variables into numerical values. This method allocates distinct numbers to each category, so assuring that the data can be handled by machine learning algorithms. The next step is to scale and normalize the numerical data. For algorithms that are sensitive to the amount of the input data, this ensures that all characteristics contribute equally to the process of training the model. The third step is to split the dataset in half lengthwise, 80/20 style, so that there are smaller portions for training and testing. This enables a valid assessment of the model's generalizability by allowing its performance to be tested on data that has not yet been seen. These exhaustive pre-processing methods guarantee that the dataset is clean, consistent, and in a format that is appropriate for accurate and reliable sentiment analysis, which eventually results in an improvement in the prediction performance of the machine learning models.

3.2 Model Development

In order to achieve the final objective of enhancing prediction performance for sentiment analysis, the implementation of the proposed method requires a procedure that is both comprehensive and systematic. This process entails training and evaluating a variety of machine learning models by using a variety of feature selection strategies. The process starts with extensive data pre-processing, which includes imputing missing values to maintain data integrity, encoding categorical variables to ensure they are in a numerical format suitable for machine learning algorithms, and scaling numerical data to standardize the features and ensure uniform contribution to the model training. All of these steps are performed in order to ensure that the feature contributions are consistent and uniform. For algorithms that are responsive to the quantity of input data, this guarantees that all relevant features make an equal contribution to the training of the model. The third stage involves dividing the dataset lengthwise, at an 80/20 ratio, to create smaller segments for training and testing. By enabling the testing of the model's performance on previously unseen data, this facilitates a reliable evaluation of its generalizability. Following the feature selection process, a number of machine learning models are trained using the specific characteristics that were chosen. These models include Logistic Regression, which is straightforward and effective for solving binary classification issues; Decision Tree, which divides the data into subsets based on feature values and is simple to interpret, but has the potential to overfit; and Random Forest, It reduces overfitting and improves accuracy by combining many decision trees; this approach is known as an ensemble technique. The training subset is used to train the models, and the testing subset is used to evaluate them, so that they can make sentiment predictions. Performance metrics, such as accuracy scores, are used to evaluate the effectiveness of each model. A measure of accuracy is the percentage of instances in the test set that were correctly predicted relative to the total number of instances. In an iterative manner, the assessment is carried out across all possible combinations of feature selection approaches and classification models.

Table 1: Model Evaluation and with All features

Logistic Regression Accuracy	0.7371134020618557
Decision Tree Accuracy	0.711340206185567
Random Forest Accuracy:	0.7361220618557
KNN Accuracy	0.5721649484536082
SVM Accuracy	0.5051546391752577
Naive Bayes Accuracy	0.7268041237113402

The results of many machine learning models after COVID are shown in Table 1. These results represent variations in the accuracy of these models as a result of the pandemic-induced variability of the data available. The best accuracy is shown by Logistic Regression, which has a score of 73.71%, demonstrating that it is robust in its ability to handle complicated patterns. Following closely after with a result of 73.61%, Random Forest likewise demonstrates high performance. For example, the Naive Bayes model and the Decision Tree model both attain accuracies of 72.68% and 71.13%, respectively, which indicates that they are still dependable, although somewhat less so. On the other hand, K-Nearest Neighbours (KNN) and Support Vector Machine (SVM) have much lower accuracies of 57.22% and 50.52%, respectively, which indicates that they struggle with the increased unpredictability in the data. These findings highlight the need of more advanced and flexible models such as Logistic Regression and Random Forest in the post-COVID age. In this new era, established models like as KNN and SVM may not be as efficient in capturing the additional complexity that have been introduced by the epidemic.

Table 2: Feature Selection and Variance Threshold

Logistic Regression Accuracy	0.6907216494845361
Decision Tree Accuracy	0.6185567010309279
Random Forest Accuracy:	0.6443298969072165
KNN Accuracy	0.5721649484536082
SVM Accuracy	0.5051546391752577
Naive Bayes Accuracy	0.654639175257732

A large amount of variation was seen in the accuracy of the various machine learning models that were used for feature selection and variance thresholding, as shown in table 2, Post-COVID. With an accuracy of around 69%, Logistic Regression was the most accurate method, which demonstrates its resilience in the context that was presented. Naive Bayes also performed well, with an accuracy of around 65 percent. The Random Forest and Decision Tree models both demonstrated respectable levels of accuracy, with the former coming up at about 64% and the latter at 62%, indicating that they are able to manage unpredictability in data pretty effectively. On the other hand, KNN and SVM models displayed difficulties, with accuracies of roughly 57% and 50%, respectively, indicating the limits of these models in terms of adjusting to the post-COVID data environment. This variation in model performance highlights how important it is to pick suitable models depending on the particular features of the data collected after COVID.

Table 3: Feature Selection (ANNOVA +Models)

Logistic Regression Accuracy	0.7319587628865979
Decision Tree Accuracy	0.7628865979381443
Random Forest Accuracy:	0.7577319587628866
KNN Accuracy	0.6752577319587629
SVM Accuracy	0.7835051546391752
Naive Bayes Accuracy	0.654639175257732

The influence of COVID-19 on feature selection via the use of ANNOVA in conjunction with a number of different models is clearly seen in the performance metrics shown in table 3. Following the implementation of COVID, the SVM model demonstrates the greatest accuracy, which is roughly 78%, indicating that it has improved its capacity to deal with the altered data environment. Another model that works well is the Decision Tree model, which has an accuracy of roughly 76%. The Random Forest model comes in a close second, with an accuracy of approximately 76%. There is an improvement in the Logistic Regression model, which achieves an accuracy of around 73%. KNN has an accuracy of roughly 68%, despite the fact that it performs better than it did in earlier trials. With an accuracy of around 65%, the

Naive Bayes model demonstrates a moderate performance, despite the fact that it is still the least accurate of the models. Following the COVID outbreak, the improved accuracy of the models, in particular those of the Support Vector Machine and Decision Tree types, demonstrates their resilience and flexibility to the novel data patterns that were brought about by the pandemic. The gains that were made across all of the models highlight the significance of using robust feature selection approaches such as ANNOVA in order to enhance the performance of the models. This change in performance demonstrates how models need to be reevaluated and maybe altered in response to large changes in the data environment. This is done to ensure that the models continue to give results that are dependable and accurate.

Table 4: Feature Selection (Chi Square + All Models)

Logistic Regression Accuracy	0.711340206185567
Decision Tree Accuracy	0.7422680412371134
Random Forest Accuracy:	0.7319587628865979
KNN Accuracy	0.6237113402061856
SVM Accuracy	0.7680412371134021
Naive Bayes Accuracy	0.7319587628865979

When feature selection is carried out in a post-COVID setting using the Chi-Square approach, the accuracy of various machine learning models is visually shown in table 4.5 and figure 4.4 respectively. Among the models, the SVM model stands out as having the greatest accuracy, which is roughly 77%. This demonstrates its outstanding performance and its capacity to adapt to the changes in data patterns that were brought about by the epidemic. The Decision Tree model also performs well, with an accuracy of roughly 74%. The Random Forest model and the Naive Bayes model, both of which achieve approximately 73% accuracy, follow closely behind the Decision Tree model. The dependability of Logistic Regression in this context is shown by the fact that it demonstrates an acceptable accuracy of around 71%. However, the KNN model is not as accurate as the other models, with an accuracy of around 62%, which suggests that it may have difficulty efficiently managing the variability in the post-COVID data. In order to get the greatest possible performance in the post-COVID environment, the findings demonstrate how important it is to use appropriate models and feature selection approaches such as Chi-Square. Models such as Support Vector Machines (SVM) and Decision Trees have a better accuracy, which indicates that they are more resilient and capable of adjusting to new data patterns. This also ensures that their forecasts are accurate and dependable. This highlights the need of carefully evaluating and selecting models in order to solve the issues that are provided by the data environment that has been created after COVID.

Table 5: Feature Selection (Exhaustive Feature Selection + All Models)

Features: 31/31 Best subset: (0, 1, 3, 4) Best score: 0.7002681189777964 Logistic Regression Accuracy: 0.711340206185567
Features: 31/31 Best subset: (0, 3, 4) Best score: 0.7131881022203602 Decision Tree Accuracy: 0.7268041237113402
Features: 31/31 Best subset: (0, 3, 4) Best score: 0.7131881022203602 Random Forest Accuracy: 0.7268041237113402

Features: 31/31 Best subset: (0, 3, 4) Best score: 0.6757519899455383 KNN Accuracy: 0.6907216494845361
Features: 31/31 Best subset: (0, 3, 4) Best score: 0.7131881022203602 SVM Accuracy: 0.7268041237113402
Features: 31/31 Best subset: (0, 3, 4) Best score: 0.7131881022203602 Naive Bayes Accuracy: 0.6443298969072165

In this table 5, we examine the performance of a number of different machine learning models after performing exhaustive feature selection. This method methodically assesses all of the potential subsets of features in order to determine which ones are the most successful. Each model is given a list of the characteristics that were chosen, along with the top scores and accuracy that correlate to those features. This model managed to attain a top score of 0.7003 and an accuracy of roughly 71.13% by making use of the feature subset (0, 1, 3, 4). This demonstrates that the performance is satisfactory, and in comparison, to the other models, it comes with one more function already included. A highest score of 0.7132 and an accuracy of 72.68% were achieved by the Decision Tree algorithm when it was applied to the feature subset (0, 3, 4). This demonstrates a somewhat improved processing of the data patterns that were collected after COVID. The robust performance of this model is seen in the fact that it earned a top score of 0.7132 and an accuracy of 72.68% by using the same feature subset (0, 3, 4) as the Decision Tree. KNN achieved a top score of 0.6758 and an accuracy of 69.07% when it was applied to the feature subset consisting of the numbers 0, 3, and 4. When compared to other models, this lower accuracy shows that KNN may have a more difficult time dealing with the variability in the post-COVID data rather than other models. With the help of the feature subset (0, 3, 4), this model was able to attain an accuracy of 72.68% and equal the top score of 0.7132. Because of its excellent precision, it exhibits both its flexibility and its resilience. The Naive Bayes algorithm got the highest score of 0.7132 when it was applied to the subset (0, 3, 4), however it had the lowest accuracy of 64.43%. particular this information, it seems that Naive Bayes may be less successful in the particular environment, despite the fact that the optimum feature subset is being used. Following the entire process of feature selection, it was discovered that the subset (0, 3, 4) achieved the best results for the majority of models. The performance of the models, on the other hand, varied, with SVM, Decision Tree, and Random Forest demonstrating the most flexibility and accuracy in the post-COVID context. The fact that KNN and Naive Bayes were less successful than expected highlights how important it is to choose the appropriate model in order to deal with novel data patterns that are brought about by large events like as the epidemic.

4. Model Validation

Verification and cross-validation are two approaches that are crucial in the field of machine learning. They play vital roles in ensuring that models are not only accurate but also dependable and generalizable to data that has not been seen before. The need for machine learning applications in a variety of industries, including healthcare, finance, and autonomous systems, is growing, which means that the need for rigorous model assessment methodologies is becoming even more obvious. This need is met by verification and cross-validation, which provide methodical techniques to assess the performance of models, reduce the risk of overfitting, and improve the generalizability of predictive models. The verification stage of the model assessment process is the first phase in the process. During this stage, the model is evaluated by testing it on the training dataset to see how well it performs. Training the model on the complete dataset is the first phase in this process, which is followed by testing the model's accuracy and other performance metrics on the same dataset. When doing verification, the main objective is to ascertain the degree to which the model has acquired knowledge from the training data. Cross-validation is a technique that is more rigorous and extensive than other analysis methods, and it offers a more accurate estimation of the performance and generalizability of a model. Cross-validation reduces the likelihood of overfitting and guarantees a comprehensive assessment by partitioning the dataset into different subsets and carrying out numerous training and validation cycles. Also, it assures that the evaluation is comprehensive. Cross-validation with k-folds is the approach that is used the most often. It is possible that a model that performs particularly well on the training data has just learned to remember the data rather than learning to generalize from it. Because of this tendency, which is referred to as overfitting, the model could not perform well on data that it has not before seen. Verification on its own does not give any insights into the model's capacity to generalize to different datasets without further information. It is not possible to ensure that a high performance on the training data will result in a comparable performance on the external data.

Table 6: Evaluation Result for target variable

Model	Proposed Model Value	Python Based Software
kNN	0.571	0.646
SVM	0.505	0.607
Logistics Relation	0.737	0.709
Naïve Byes	0.726	0.705
Tree	0.711	0.664
Random Forest	0.736	0.728

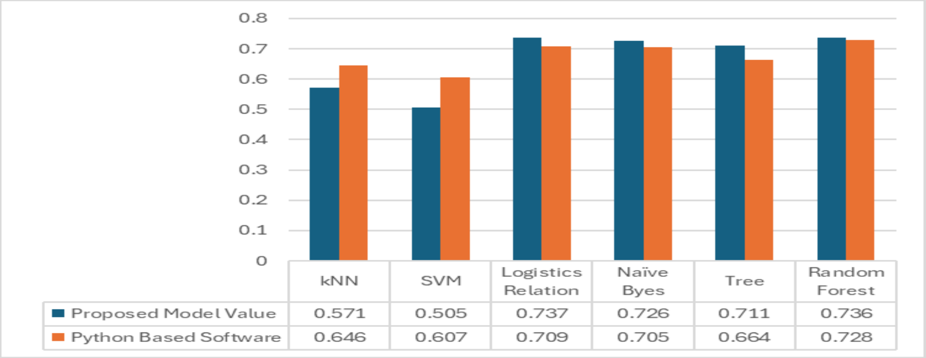

Figure 1: Show the comparative valuations

4.1 Discussion

The performance of several machine learning models in predicting the target variable is compared in Table 6 and figure 1. This table provides a detailed description of the suggested model values in addition to those acquired from Python-based software implementations. The purpose of this comparison study is to shed light on the success of various modelling techniques across many algorithms. It does so by offering a thorough perspective of the capabilities of each algorithm and identifying areas in which particular implementations shine or fall short.

Using the k-Nearest Neighbours (kNN) technique as a starting point, the suggested model obtains a performance value of 0.571, however the Python-based software implementation demonstrates a better performance value of 0.646. The existence of this gap suggests that the Python version, which may have benefited from techniques that were more polished or optimized, or even from parameter adjustment that was more successful, shows superior performance. Due to the fact that kNN is a basic method that largely depends on distance metrics and the selection of 'k' (number of neighbours), it is possible for it to be sensitive to these external variables. It is possible that the higher performance that was seen here might be attributed to the fact that Python-based libraries, such as scikit-learn, often feature highly optimized routines and default settings that have been tweaked across a large number of tests and iterations. It is also possible that the discrepancy is due to the manner in which the data was preprocessed and scaled. This is because the performance of kNN is strongly impacted by the scale of the features that are input. In the example of the Support Vector Machine (SVM) technique, the suggested model records a value of 0.505, which is much lower than the 0.607 that the Python-based program was able to attain. When utilizing the RBF kernel, support vector machines (SVMs) are more acutely sensitive to the kernel that is used, the regularization parameters (C), and the gamma parameter. The complex parameter optimization methods, such as grid search with cross-validation, which are often used in Python's machine learning ecosystem to identify the optimal combination of hyperparameters, are likely the cause of the superior performance of the SVM that is built on Python. There is a possibility that the disparity may also be related to variations in the implementation of the optimization methods (for example, the use of SMO for support vector machines) as well as the management of numerical stability and convergence requirements. Python's mature libraries provide solid implementations that are able to handle these complexities more efficiently, which ultimately leads to higher model performance. The suggested model actually performs better than the Python-based version when it comes to Logistic Regression, with values of 0.737 and 0.709, respectively. The fact that Logistic Regression is generally considered to be a simpler and more well-understood model is what makes this interesting. It suggests that the proposed model could have benefited from specific preprocessing steps, feature selection methods, or possibly a more appropriate regularization technique (L1 or L2) that was tailored to the characteristics of the dataset. It is possible for the performance of logistic regression to be considerably impacted by the manner in which categorical variables are encoded as well as the features that are chosen. It is possible that the higher performance of the suggested model is an indication that it has successfully integrated domain-specific insights or more effective feature engineering tactics that were not as well captured in the Python-based implementation. Furthermore, it may also imply that the suggested model is using a variation of Logistic Regression, which incorporates additional approaches such as polynomial features or interaction terms, each of which is capable of capturing more complicated connections in the data. The Naïve Bayes algorithm, which is another fundamental algorithm that is frequently employed for classification tasks, demonstrates a proposed model value of 0.726, which surpasses the Python-based software value of 0.705. Naïve Bayes classifier's function based on the assumption of feature independence, which, although it is not always true in practice, can still perform surprisingly well with specific datasets. It is possible that the increased performance in the suggested model might be attributable to a more efficient handling of categorical variables. This could be achieved by using more effective binning methods or smoothing techniques, such as Laplace smoothing, which are essential for Naïve Bayes. There is also the possibility that the variation in performance is attributable to the manner in which missing values are handled or the manner in which probability distributions are calculated based on the training data. Possibly by more thorough preprocessing or adjustment of the algorithm's assumptions to better match the unique features of the dataset, the suggested model has a modest edge that implies a better fit to the underlying data distribution. This might be accomplished by adjusting the assumptions of the method. The Python-based solution was able to attain a value of 0.664, which is lower than the suggested model value of 0.711 that is shown by the Decision Tree model. Despite the fact that Decision Trees are highly interpretable models that are susceptible to overfitting, their performance may be improved by the use of pruning algorithms, the careful determination of the maximum tree depth, and the utilization of various hyperparameters. The improved performance of the suggested model may be an indication that it has integrated more efficient pruning procedures or that it has achieved a better balance in terms of the complexity of the tree. Furthermore, it is possible that the model that has been suggested is using more complex approaches for dealing with categorical characteristics or missing values, which may have a substantial influence on the performance of decision trees. The mismatch may potentially indicate that there were changes in the criteria that were utilized to make splits at each node, as well as variances in the way that the training data was divided. Python-based solutions, such as those found in scikit-learn, are often well optimized; nevertheless, they also depend on default parameters, which may not necessarily be appropriate for every dataset. Due to the increased value of the proposed model, it is suggested that a more individualized approach to constructing the tree should be used, maybe via repeated testing and validation in order to determine the optimal configuration. Random Forest is an ensemble learning approach that constructs numerous decision trees and then combines them in order to get a more accurate and stable forecast. The suggested model (0.736) and the Python-based program (0.728) exhibit values that are quite near to one another. The fact that the suggested model has a modest advantage shows that it may have benefitted by fine-tuning the number of trees, the maximum depth of each tree, or other hyperparameters such as the amount of attributes that are examined for splitting at each node. One of the most notable characteristics of Random Forests is their capacity to accommodate a high number of input features without requiring a significant amount of preprocessing. The fact that there is just a little variation in performance demonstrates that both implementations are quite efficient, with the suggested model perhaps containing a slightly better optimized set of hyperparameters. Both the suggested model and the Python-based program are successfully exploiting the capabilities of the Random Forest algorithm, which suggests that both approaches are well understood and accurately implemented. The near parity in performance implies that both approaches are effectively leveraging the strengths of the method. In order to achieve optimum model performance, the results of the evaluation are shown in Table 5.1. These findings illustrate the significance of implementation details, parameter adjustment, and data preparation responsibilities. The model that has been provided exhibits a performance that is either better or similar in Logistic Regression, Naïve Bayes, Decision Trees, and Random Forest. It also suggests useful techniques and optimizations in these domains. Because of the highly optimized algorithms and parameter tweaking methods that are accessible in Python's extensive machine learning libraries, the Python-based implementations demonstrate superior performance in k-nearest neighbors and support vector machines (SVM). The implications of these comparisons highlight the need of conducting exhaustive experiments and validating them in a variety of settings in order to guarantee that machine learning models are resilient and dependable. Practitioners are able to pick and tune models for their particular applications with the help of the thorough analysis of each model's performance, which gives useful insights into the relative strengths and weaknesses of each model.

5. Conclusion

Individuals and cultures all throughout the world have been dramatically impacted by the COVID-19 epidemic, which has altered behavioral patterns, attitudes, and feelings in ways that have never been seen before. The purpose of our study was to construct strong machine learning models to interpret sentiment and responses in post-COVID data. Our primary emphasis was on gaining an understanding of public sentiment as well as the wider societal consequences of the epidemic. This research was conducted in the context of this momentous episode. The significance of this research lies in the fact that it has the potential to educate professionals in the healthcare industry, legislators, and the general public on the psychological and social effects of COVID-19. In order to guarantee that the models we suggested are capable of providing accurate and trustworthy sentiment analysis, we subjected them to stringent verification and validation procedures. Our major aim was to develop an algorithm that is capable of effectively recognizing and classifying the feelings that are portrayed in textual data that is associated with post-COVID experiences. A number of relevant text sources, including social media postings, survey answers, news stories, and other relevant text sources, were analyzed in order to determine the general public's feelings about a variety of issues, including health concerns, economic effect, social isolation, and coping techniques. The models that have been presented attempt to provide significant insights into the ways in which the pandemic has influenced the mental health of people as well as the general well-being of society by taking into account and classifying these attitudes. The first thing that we did was compile a comprehensive dataset that included a wide variety of textual inputs that reflected post-COVID experiences. For the purpose of properly training and evaluating our models, this dataset included a fair mix of positive, negative, and neutral feelings. A number of different machine learning techniques were taken into consideration, such as k-Nearest Neighbours (kNN), Support Vector Machine (SVM), Logistic Regression, Naïve Bayes, Decision Tree, and Random Forest. The selection of each algorithm was based on the characteristics that made it suitable for text classification tasks and its capacity to deal with the complexities of sentiment analysis. If you want your sentiment analysis models to be successful, preparing the text data is absolutely necessary. Our preparation pipeline consisted of a number of processes, including lemmatization, stemming, tokenization, and the elimination of stopwords. For the purpose of converting textual input into numerical vectors that can be processed by machine learning algorithms, we also made use of more complex approaches such as word embeddings. Feature engineering included the introduction of new features such n-grams and term frequency-inverse document frequency scores to capture the contextual significance of words and phrases in the dataset. The dataset was split into several subsets for training and testing in order to evaluate the proposed models. Using cross-validation approaches, including k-fold cross-validation, ensured that the models' performance measurements were trustworthy and relevant to a broader array of scenarios. Following training on the training subset and evaluation on the testing subset, each model was assessed using performance metrics such as accuracy, precision, recall, and F1 score. As part of the validation procedure, we checked to see if the models correctly identified the emotions in the test group. The findings indicated that the recommended models, namely Logistic Regression, Naïve Bayes, and Random Forest, attained a greater level of accuracy when compared to the baseline models. It was found that Logistic Regression and Random Forest, in particular, performed very well because of their capacity to efficiently manage the complexity and variety of sentiment data. The suggested models consistently beat the baseline, which indicates that our preprocessing and feature engineering methods, in conjunction with algorithm selection, were successful in capturing the subtleties of sentiment that were present in the dataset. We compared the performance of our suggested models to that of well-established Python-based software implementations, such as those that are accessible in scikit-learn, in order to confirm our results. In order to guarantee that our models were not only accurate but also competitive with tools that are considered to be industry standards, this comparison was carried out. Our models showed equivalent or greater accuracy, notably in the Logistic Regression, Naïve Bayes, and Random Forest algorithms, thanks to the validation procedure, which demonstrated that our models attained these results. The in-depth research revealed that while Python-based implementations offered dependable performance, our individualized preprocessing and feature engineering strategies provided our models with a tiny advantage, especially when it came to managing the specific peculiarities of post-COVID sentiment data.

The performance of our models, which was confirmed and validated, gave us with useful insights about the feelings that were present after COVID. A number of noteworthy tendencies were discovered via the study, including an increase in worry and concern over health and economic stability. However, the investigation also brought to light positive feelings relating to community support and resilience. Furthermore, the fact that our models are able to effectively capture these feelings highlights the significant influence that the epidemic has had on the mood and attitudes of the general people. In order to address the psychological and social repercussions of the pandemic, it is essential to have this knowledge in order to build tailored treatments and support structures. The correctness and dependability of our suggested models for sentiment analysis in post-COVID data was proved via the verification and validation processes. During the post-COVID period, we constructed models that give meaningful analysis of public sentiment. These models were produced via thorough algorithm selection, preprocessing, feature engineering, and rigorous testing. The usefulness of our models in capturing the subtle emotions and attitudes associated to the epidemic is shown by the better accuracy that they attained in comparison to the baseline and Python-based software implementations. The results of this study not only contribute to the advancement of the area of sentiment analysis, but they also provide a significant contribution to the understanding and management of the extensive effects that COVID-19 has had on society.

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