INTERNATIONAL JOURNAL OF LATEST TECHNOLOGY IN ENGINEERING, MANAGEMENT & APPLIED SCIENCE (IJLTEMAS)

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

Sentiment Analysis of COVID 19 Tweets using Optimize LSTM Model

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DOI : https://doi.org/10.51583/IJLTEMAS.2025.1412000110

Received: 27 December 2025; Accepted: 01 January 2026; Published: 10 January 2026

ABSTRACT

The popularity of social media has increased curiosity in psychology, mental health, and human circumstances. Twitter and other social media platforms have been utilised for data collection, personality type prediction, and sentiment analysis during emergencies. Deep learning techniques examine both positive and negative feelings. The retrieval of Covid 19 tweets, both positive and negative, is not perfect, and low accuracy may lead to the detection of unidentified tweets from social sites. The objective is to improve the retrieval and comparison of pertinent Covid 19 positive and negative tweets in terms of precision, recall, and train/validation accuracy. A LSTM is defined by a sequence of layers, with the first layer defining inputs. The ADAM optimization algorithm updates weights, and the model is evaluated. The proposed model for sentiment content categorization from tweets uses LSTM-ADAM approaches, with a 78% accuracy rate compared to the 76% accuracy of SVM methodology. It supports manual participation and accepts text information in any format.

Keywords: Covid-19, LSTM, ADAM, Accuracy.

INTRODUCTİON

Social scientists and psychologists have been interested in the unheard-of proliferation of information on social media in order to get a deeper knowledge of psychology, mental health, and the human condition. Researchers in psychology and behavioural science have utilised social media sites like Twitter as a means of gathering data (Zimbra et al., 2018). It has also been used to the prediction of personality types and the analysis of internet user patterns and backgrounds. It's also intriguing to see how individuals communicate their feelings in response to terrible occurrences like terrorism, strong political opinions, and natural catastrophes. For example, during the Kenyan terror assault, Twitter served as a vital conduit for information sharing between the public, emergency response team, and government (Wang et al., 2012).

Sentiment analysis is the focus of the linguistics and natural language processing area of opinion mining. In order to analyse and extract opinions and emotions from textual data, it assesses the degree of polarity of words and phrases. Numerous research projects and innovations have been undertaken by institutions or individuals seeking to understand public opinion on a particular subject. Furthermore, a significant amount of research has been done on more application-focused methodologies. Moreover, assessing Twitter conversations has been a fruitful field of research (Bing et al., 2012). The talk may help individuals comprehend each other's sentiments since it provides a plethora of discriminative information pertinent to a range of issues. Using a revolutionary deep learning method, the positive and negative emotions exhibited in Twitter chats were analysed. To determine the sentiment polarity of social media messages, it combined modules for dialogue reconstruction with emotion recognition. Currently assessed the dissemination of information across platforms by examining Twitter exchanges. created forecasting models using a latent variables-based searching approach to anticipate the presence of viruses based on the workload of Twitter chats (Adwan et al., 2020).

In particular, SA is covered in great detail in this work and is divided into the following subsections: In Section 2, the history of SA of Twitter data is shown. The issue identification of sentiment analysis is shown in Section

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3. Section 4 explains the study aims, and Section 5 provides an overview of the SA approach using data from Twitter. Results and current developments in Twitter sentiment analysis are shown in Section 7.

BACKGROUND

Social studies and business have also used sentiment analysis. In order to support their industrial and commercial operations, corporations such as Google and Microsoft have lately developed their own sentiment analysis tools (Bollen et al., 2011). Sentiment analysis (SA) aims to tackle the challenge of assessing the implicit meaning found in tweets sent on Twitter, which is regarded as a novel topic. There are several obstacles to SA, the biggest of which is the message size limitation (Meng et al., 2022). Because a tweet may only be 140 characters long, it can be challenging to understand the meaning in that small space. Concurrently, the disorganised textual display on Twitter adds to the complexity. Thus, the recommended SA techniques need to address a number of issues (Pak et al., 2010). The typical SA operation flow is shown in Figure 1.

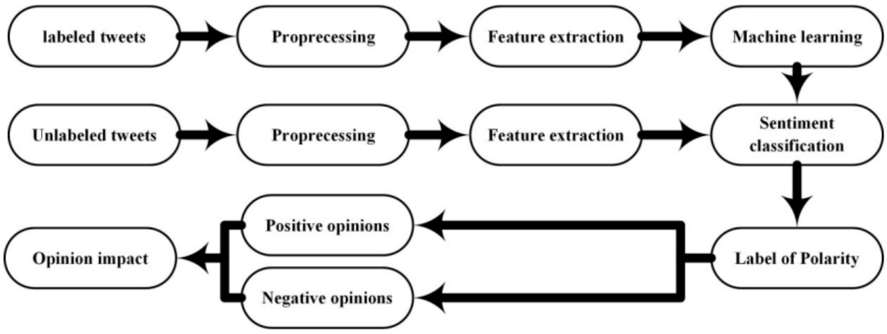

Figure 1. The Operation Flow of Sentiment Analysis of Twitter Data (Giachanou et al.; 2016).

Three basic categories may be used to categorise sentiment analysis methodologies: lexicon-based, machine learning-based, and hybrid techniques. Figure 2 [41] depicts the sentiment analysis taxonomy.

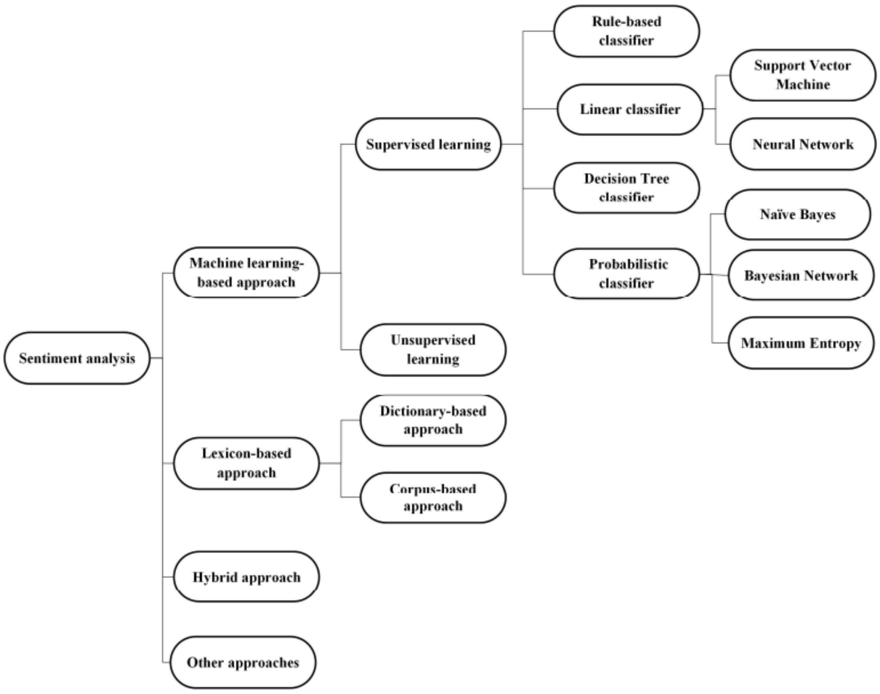

Figure 2. The taxonomy of sentiment analysis (Jose et al.; 2010)

In sentiment analysis, the classification step makes use of a classifier that has been trained using machine learning methods. The two main categories of this method are supervised learning and unsupervised learning. Table 1 provides a comprehensive publication using machine learning approaches.

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Table 1. The list of machine learning-based approaches for sentiment analysis.

Ref	Objective and Algorithm Used	Data Scope	Dataset
[11]	Feature selection, CRF, and particle swarm optimisation (PSO)	Reviews of laptops and restaurants	2014 SemEval
[12]	Logistic regression model, discrete PSO, and feature subset selection	Money-related, spam-based, childcare, etc.	ML Respository at UCI
[13]	NB, SVM, CART, Binary PSO, and feature selection	Numbers typed by hand	UCI benchmark datasets
[14]	Choosing affective traits, multi-swarm PSO, SVM	Course Evaluation	Collections from MOOC
[15]	NB, SVM, LR, feature weighting, optimization-based weighted voting method, Logistic regression in Bayesian analysis and linear discriminant	TV, radio, medication, camera, etc.	datasets taken from online sources
[16]	SVM and binary categorization	Review of a film	Own
[17]	feature weighting and Kullback-Leibler divergence, SVM flexibility score	Newspaper article, MPQA dataset	Polarity dataset, Subjectivity dataset, and movie review NB, SVM
[18]	feature selection and weighting	movie review	IMDb

Table 2. The list of lexicon-based approaches proposed for sentiment analysis.

Ref	Objective and Algorithm Used	Data Scope	Dataset
[19]	Text classification employing finely tuned attitude labels, taxonomy	User-generated personal story	Dataset from Experience Project website
[20]	lexicon produced by self-development, semantic lexicon produced by document discourse structure, sentiment classifier	Movie review	IMDB
[21]	NLP, PMI-IR, and a syntax-based comments-oriented news sentiment analyzer	News information	N/A
[22]	Comparison of supervised versus lexical knowledge-based approaches for emotion detection using SVM	Corpus of emotions	ISEAR, Emotinet
[23]	Emotion lexicon and affect-based search	Books, stories, emails, and so	Corpus of enron

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	using crowdsourcing	forth	email
[24]	Rule-based classifier in an unsupervised SSA-UO system	Unlabeled SMS and Twitter messages	SemEval
[25]	Rule-based classifier and rule-based pattern matching system	Twitter and SMS messages	SemEval
[26]	Emotional triggers and sentiment vocabulary for unsupervised sentiment analysis	Tweet message	STS, OMD
[27]	Sentiment analysis at the tweet, entity, and generic sentiment lexicon levels	Tweet message	OMD, HCR, STS-Gold
[28]	Connotative polarity detection and a vocabulary of connotations	Tweet message	SemEval-2007, Sentiment twitter

Problem Identification

The problems identified by previous research (Kulkarni et al., 2022; Swathi et al., 2022) are as follows:

• It is not always possible to identify pertinent Covid 19 tweets via retrieval.

• It is not always possible to distinguish between positively and negatively tagged tweets.

• Due to their limited accuracy, unrecognised tweets from social media platforms may be detected.

Research Objectives

The aims of the suggested work are as follows:

• To increase accuracy so that pertinent Covid 19 positive and negative tweets are perfectly retrieved.

• To enhance recollection throughout the retrieval procedure for perfectly relevant Covid 19 positive and negative tweets.

• To increase the exactness of the train and validation accuracy in comparison to the corresponding train and validation loss.

METHODOLOGY

The algorithm of proposed model is as follows:

Step 1. Define Network

Keras defines a neural network as a structure composed of several layers arranged in a hierarchical manner. The Sequential class encompasses many levels. To begin, instantiate an object of the Sequential class. Subsequently, you may proceed to generate your layers and organize them in the appropriate sequence for further linkage. The LSTM () function refers to the recurrent layer of the LSTM, which consists of memory units. The Dense () layer is often positioned after LSTM layers and is used for generating prediction outputs via complete connectivity. The number of inputs that should be anticipated must be explicitly defined in the top layer of the network. Input of three-dimensional data is required, which includes samples, timesteps, and attributes.

• Examines. The rows in your data are these.

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• Steps in time. These are historical data points for a feature, like lag variables.

• Qualities. The columns in your data are these.

Step 2. Compile Network

We must assemble our network once it has been defined.

One step towards efficiency is compilation. It turns the simple layer sequence we established into a very effective set of matrix transformations in a format that can run on your CPU or GPU, depending on how Keras is set up.

Step 3. Update and Optimize Weight

Once the network is put together, it may be fit by use a training set of data to modify the weights.

Use the effective ADAM (Adaptive Moment Estimation) optimisation technique to update the weights. For stochastic gradient descent (SGD)-based optimisation in machine learning, the Adam optimizer is an iterative optimisation technique. The adaptive learning rate algorithm ADAM was created to accelerate convergence and increase training rates in deep neural networks.

Step 4. Fit Network

To fit the network, the training data must be provided. It comprises of a matrix of input patterns, X, and an array of matching output patterns, y.

The network is trained using the backpropagation method, and it is optimised using the loss function and optimisation strategy selected during model compilation.

To apply the backpropagation approach, the network has to be trained for a certain number of epochs, or exposures, to the training dataset. Batches, or sets of input-output pattern pairings, may be created from each epoch. This indicates how many patterns the network sees before updating the weights throughout an epoch. In addition, it optimises efficiency by limiting the number of input patterns that are loaded into memory at once.

Step 5. Evaluate Network

After it has been trained, the network may be evaluated.

Since the network has previously seen all of this data, it may be evaluated using the training set, but this won't provide a useful indication of how well the network works as a predictive model.

An alternate dataset that wasn't utilised for testing might be used to evaluate the network's performance. In the case of unobserved data, this will provide an estimate of the network's prediction performance.

In addition to any other metrics (such classification accuracy) that were provided during model compilation, the model evaluates the loss over all test patterns. A set of evaluation metrics is returned.

Step 6. Make Predictions

If we are happy with our fit model's performance, we could utilise it to make predictions on new data. To do this, just call the model's predict() method with a range of new input patterns.

Experiment and Result

This section outlines the precise procedures of the experiment after outlining various presumptions and constraints. The following are the presumptions made in this work:

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(1) The training and testing data come from a single dataset, and our study focuses on sentiment analysis of COVID-19 tweets. When using the ant dataset for experimentation, for instance, the training set is chosen and the test set is created from the remaining portion of the dataset.

(2) The trained model favours the negative tweets classes during the trials due to a limited number of faulty classes. Thus, before training the model, class imbalance is applied to the whole dataset.

(3) An optimisation algorithm called ADAM (Adaptive Moment Estimation) is employed to more accurately evaluate the method performance.

The correctness of the sentiment analysis paradigm suggested in this study may be confirmed under the aforementioned presumptions. The particular protocol for the experiment is as follows:

Step 1: The software's class dependency is extracted using the code analysis tool, and a CSV file is subsequently created.

Step 2: The covid 19 tweets dataset is used to extract the labelled nodes and feature metrics for each node.

Step 3: To address the imbalance in data classes, the LSTM-ADAM technique is used.

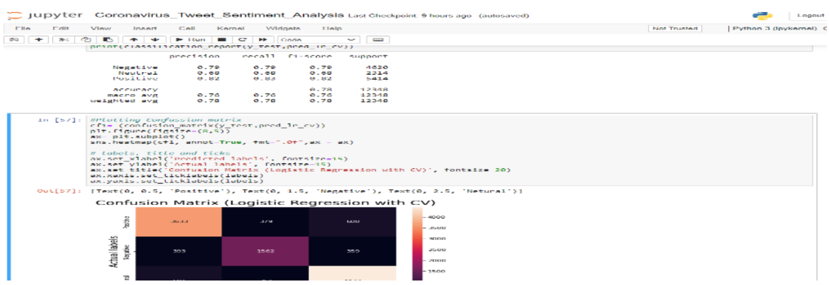

Figure 3. Calculation of confusion matrix, precision, recall, F1-Score and accuracy among different models and LSTM-ADAM (Proposed Model)

Table 4: Estimation of Sentiment Parameters using LSTM-ADAM (Proposed Model)

Sentiment Parameter	Count
Positive	11422
Negative	9917
Neutral	7713
Extremely Positive	6624
Extremely Negative	5481

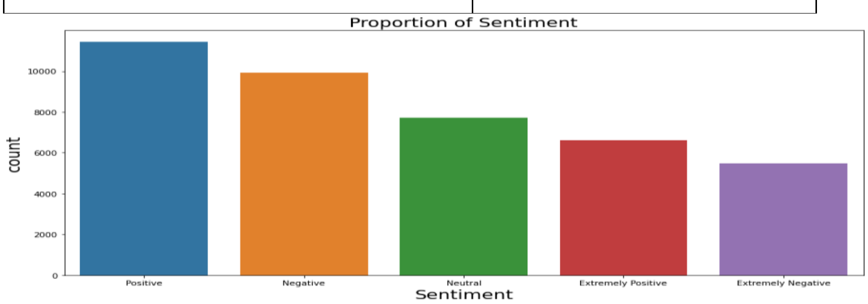

Figure 4. Graphical Analysis of Sentiment Parameters using LSTM-ADAM (Proposed Model)

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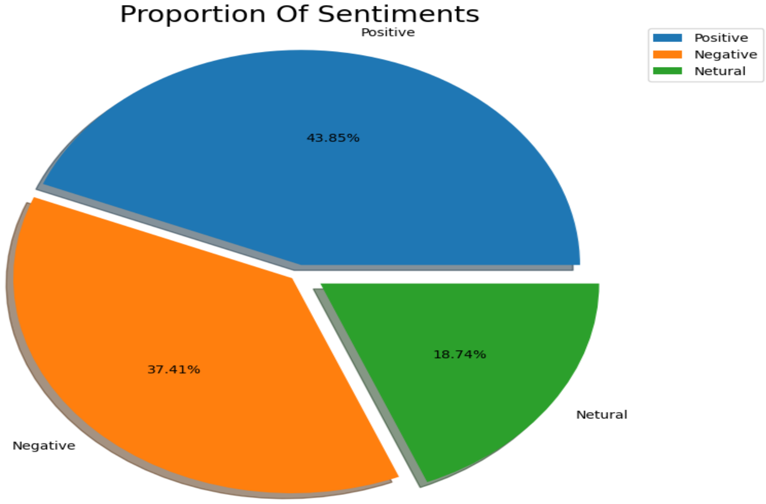

Figure 5. Spherical Analysis of Sentiment Proportions LSTM-ADAM (Proposed Model)

Table 5. Estimation of Precision, Recall and F1-Score among different models and LSTM-ADAM (Proposed Model) for Negative Tweets

Models	Precision	Recall	F1-Score
KNN	0.55	0.40	0.46
Decision Tree	0.69	0.68	0.68
SVM	0.77	0.75	0.76
XG Boost	0.7	0.6	0.79
LSTM-ADAM (Proposed Model)	0.79	0.79	0.79

Figure 6. Graphical Analysis of Precision among different models and LSTM-ADAM (Proposed Model) for Negative Tweets

The above graph show that the proposed model gives better precision for negative tweets as compare than other models. The precision of LSTM-ADAM (Proposed Model) is improve by 0.02 as compare than SVM prediction model.

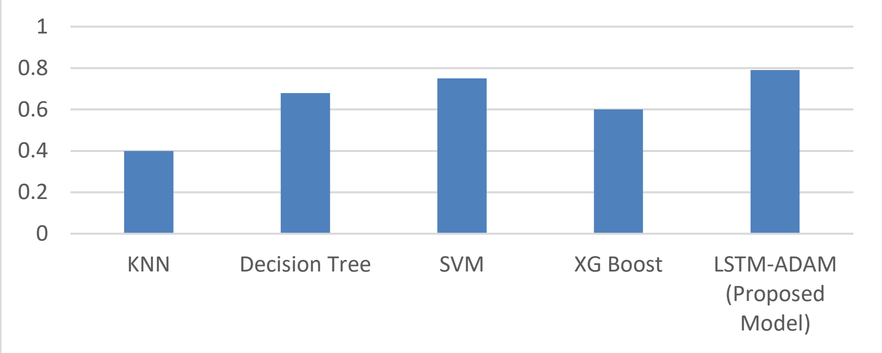

Figure 7. Graphical Analysis of Recall among different models and LSTM-ADAM (Proposed Model) for Negative Tweets

The above graph show that the proposed model gives better recall for negative tweets as compare than other models. The recall of LSTM-ADAM (Proposed Model) is improve by 0.04 as compare than SVM prediction model.

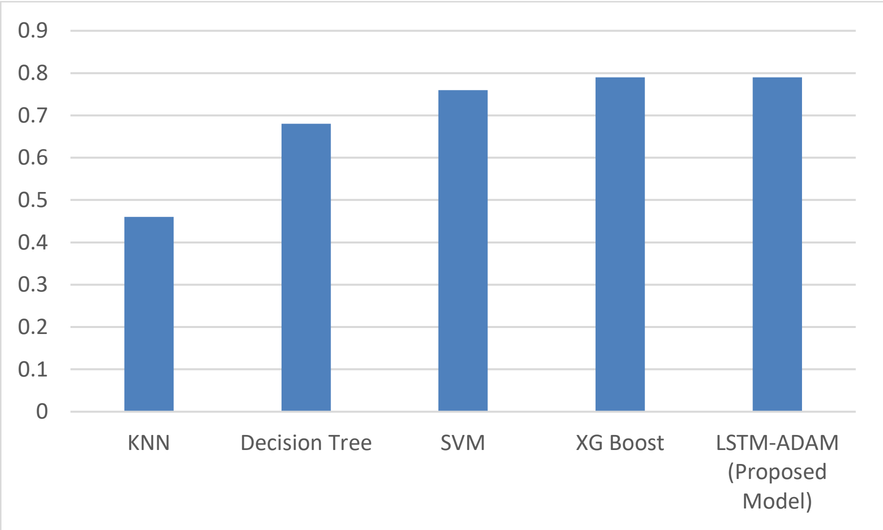

Figure 8. Graphical Analysis of F1-Score among different models and LSTM-ADAM (Proposed Model) for Negative Tweets

The above graph show that the proposed model gives better F1-Score for negative tweets as compare than other models. The F1-Score of LSTM-ADAM (Proposed Model) is similar to XG Boost Classifier model.

Table 6. Estimation of Precision, Recall and F1-Score among different models and LSTM-ADAM (Proposed Model) for Neutral Tweets

Models	Precision	Recall	F1-Score
KNN	0.25	0.72	0.37
Decision Tree	0.62	0.67	0.64
SVM	0.65	0.66	0.66
XG Boost	0.75	0.65	0.68
LSTM-ADAM (Proposed Model)	0.68	0.68	0.68

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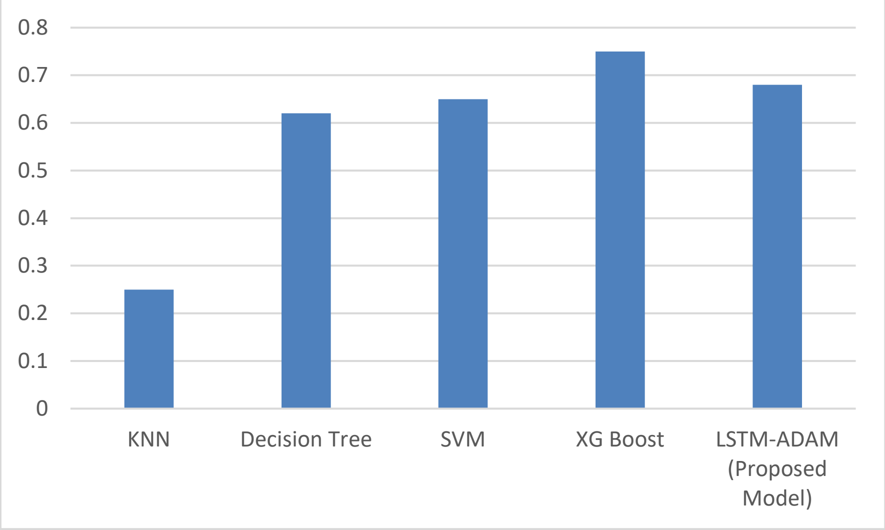

Figure 9. Graphical Analysis of Precision among different models and LSTM-ADAM (Proposed Model) for Neutral Tweets

The above graph show that the XG-Boost model gives better precision for neutral tweets as compare than other models.

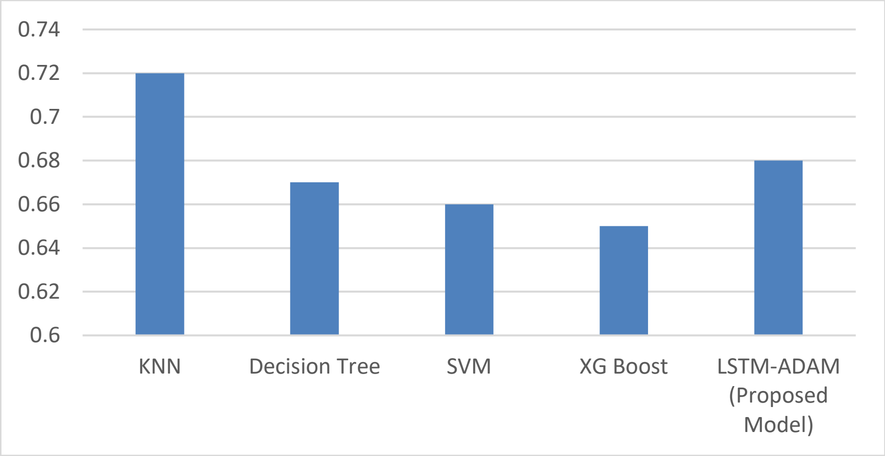

Figure 10. Graphical Analysis of Recall among different models and LSTM-ADAM (Proposed Model) for Neutral Tweets

The above graph show that the KNN model gives better recall for neutral tweets as compare than other models.

Figure 11. Graphical Analysis of F1-Score among different models and LSTM-ADAM (Proposed Model) for Neutral Tweets

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The above graph show that the proposed model gives better F1-Score for neutral tweets as compare than other models. The F1-Score of LSTM-ADAM (Proposed Model) is similar to XG Boost Classifier model.

Table 7. Estimation of Precision, Recall and F1-Score among different models and LSTM-ADAM (Proposed Model) for Positive Tweets

Models	Precision	Recall	F1-Score
KNN	0.69	0.29	0.41
Decision Tree	0.75	0.74	0.75
SVM	0.8	0.81	0.8
XG Boost	0.55	0.86	0.67
LSTM-ADAM (Proposed Model)	0.82	0.83	0.82

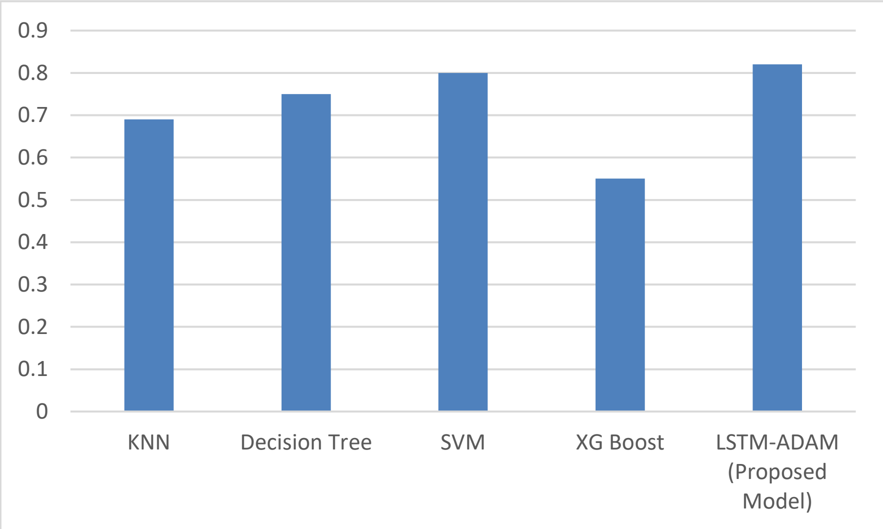

Figure 12. Graphical Analysis of Precision among different models and LSTM-ADAM (Proposed Model) for Positive Tweets

The above graph show that the proposed model gives better precision for positive tweets as compare than other models. The precision of LSTM-ADAM (Proposed Model) is better than SVM Classifier model.

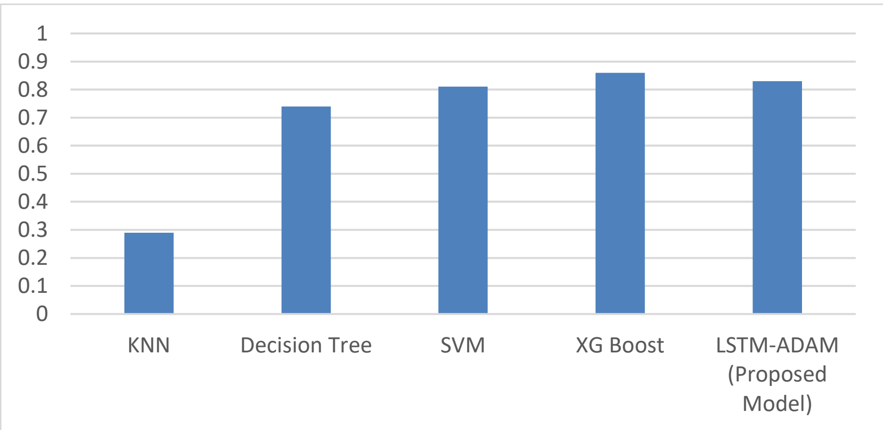

Figure 13. Graphical Analysis of Recall among different models and LSTM-ADAM (Proposed Model) for Positive Tweets

The above graph show that the XG-Boost model gives better recall for positive tweets as compare than other models.

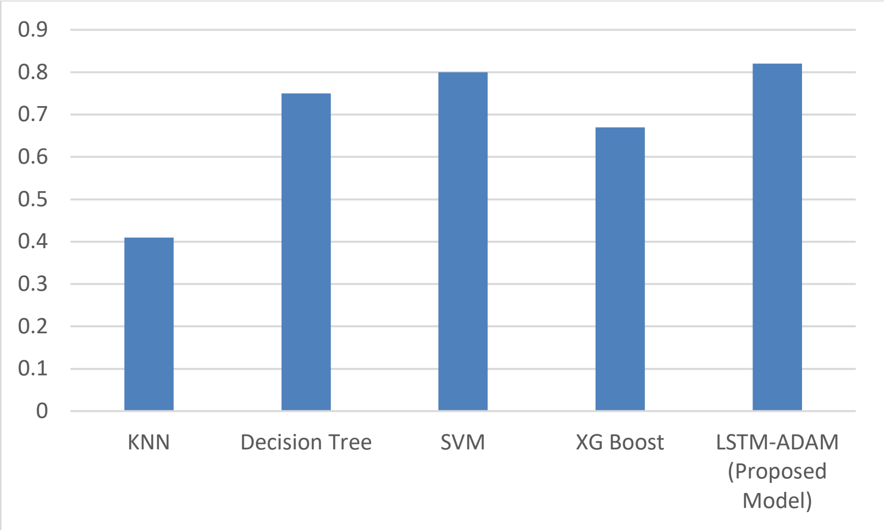

Figure 14. Graphical Analysis of F1-Score among different models and LSTM-ADAM (Proposed Model) for Positive Tweets

The above graph show that the proposed model gives better F1-Score for positive tweets as compare than other models. The F1-Score of LSTM-ADAM (Proposed Model) is better than SVM model.

Table 8. Estimation of Accuracy among different models and LSTM-ADAM (Proposed Model) for Positive Tweets

Models	Accuracy
KNN	0.41
Decision Tree	0.7
SVM	0.76
XG Boost	0.6
LSTM-ADAM (Proposed Model)	0.78

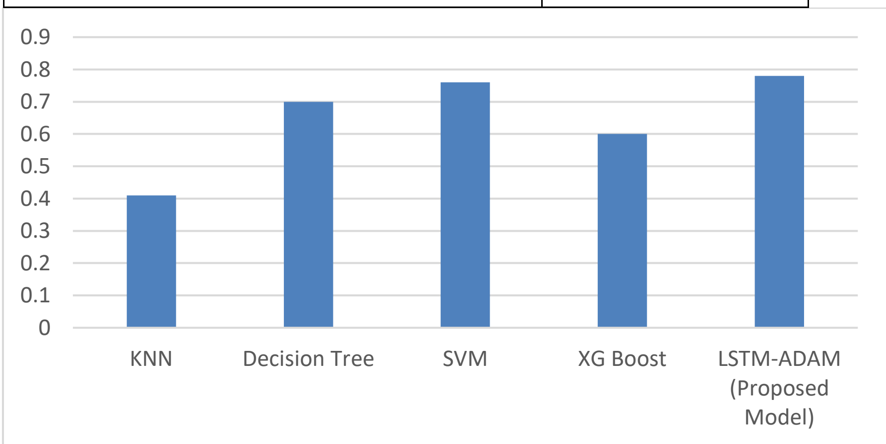

Figure 15. Graphical Analysis of Accuracy among different models and LSTM-ADAM (Proposed Model) for Covid-19 Tweets

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The above graph show that the proposed model gives better accuracy for covid 19 tweets as compare than other models. The accuracy of LSTM-ADAM (Proposed Model) is better than SVM Classifier model.

CONCLUSİONS

Researchers should focus on this topic because of the significant rise of digital text data on servers and libraries. In light of this, study has concentrated on the problem of content sentiment identification. Although a great deal of research has previously been done in this area, it has only focused on semi-automated sentiment categorization. The suggested improvement will improve the work's sentiment detection effectiveness across all assessment metrics. The whole model uses dictionaries to preprocess the input before pulling patterns and keywords from it. The learning model's accuracy increases with the decrease of the input feature set, where a geo-inspired technique yields a high-quality vector set. Therefore, it is anticipated that the study will provide a model that identifies the sentiment of tweet content where the material does not need any structure and the algorithm's execution time is also quite short.

The following are the thesis work's conclusions:

• Lemmatizing and stemming text material from tweets to achieve ideal sentiment content categorization.

• The suggested model supports any manual participation for sentiment recognition; • The LSTM model may accept text information in any format;

• The ADAM approach is used to optimise the learning model by decreasing the feature vector. While the SVM methodology has an accuracy of around 76%, the suggested method (LSTM-ADAM) has an accuracy of 78%.

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ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue XII, December 2025

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