Available online at http://icsejournal.com/index.php/JCSE
Journal of Computer Science and Engineering (JCSE)
e-ISSN 2721-0251
Vol. 3, No. 2, August 2022, pp. 107-119

Novel approach of Predicting Human Sentiment using Deep Learning

Ebtesam Shadadi[1*], Shama Kouser[2], Latifah Alamer[3], Pawan Whig[4]

[1,2,3] Jazan University, Al Maarefah Rd , Jazan 45142, Saudi Arabia
[4] Vivekananda Institute of professional studies, New Delhi, Delhi 110034, India
[1] ashedadi@jazanu.edu.sa*; [2] skouser@jazanu.edu.sa; [3] laalamer@jazanu.edu.sa; [4] pawanwhig@gmail.com
* corresponding author

ARTICLE INFO

Article History:
Received Juny 24, 2022
Revised July 31, 2022
Accepted August 25, 2022

Keywords:
Tweet;
Machine Learning;
Sentiment;
Lexicon

Correspondence:
E-mail: ashedadi@jazanu.edu.sa

ABSTRACT

Due to its interactive and real-time character, gathering public opinion through the analysis of massive social data has garnered considerable attention. Recent research have used sentiment analysis and social media to do this in order to follow major events by monitoring people's behavior. In this article, we provide a flexible approach to sentiment analysis that instantly pulls user opinions from social media postings and evaluates them. As time passed, an increasing number of people shared their opinions on social media. More individuals can now communicate with one another as a result. Along with these advantages, it also has certain drawbacks that cause resentment in some people. Hate speech is another possibility. Hate speech impacts the community when it contains insulting or threatening language. Before it spreads, this kind of speech has to be identified and deleted from social media platforms. The process of determining whether a text's feelings reflect hatred or not involves sentiment analysis. Python language was used to analyze the Twitter dataset. There were 5000 Tweets in total in this dataset, and we used deep learning to improve the machine learning model's accuracy. The experimental outcome in both cases of the Twitter dataset uses the Random Forest approach, which has a 99 percent accuracy rate.

1. Introduction

Presently, people communicate their ideas and beliefs differently thanks to the internet. Today, the primary channels for doing so include blogs, forums, websites that let users provide product reviews, social media, etc. Social networking services like Facebook, Twitter, Google Plus, and others are used by millions of individuals today to express their feelings, opinions, and share insights about their everyday lives[1]. Internet forums provide us with interactive media where users may use forums to inform and persuade others. Tweets, status updates, blog posts, comments, reviews, and other types of social media content provide a lot of sentiment-rich data. Additionally, social media gives businesses a chance by offering them a platform to engage with their consumers for advertising. People heavily rely on user-generated content from the internet when making decisions[2]. For instance, if someone wants to purchase a good or utilise a service, they will research it online and debate it on social media before making a choice. A typical user cannot analyse the large volume of user-generated content. Since this needs to be automated, several different sentiment analysis approaches are in use[3]

The processing, searching, or analysis of the factual material that is provided is the core goal of textual information retrieval strategies. Even if facts have an objective component, certain other literary elements exhibit subjective traits. Sentiment Analysis's fundamental components opinions, sentiments, assessments, attitudes, and emotions are primarily represented by these contents[2]. Due in large part to the enormous expansion of information available online from sources like blogs and social networks, it presents numerous difficult chances to build new applications[3].

http://dx.doi.org/10.36596/jcse.v3i2.533

For instance, by using SA and taking into account factors like favourable or negative thoughts about the goods, suggestions of things provided by a recommendation system may be anticipated.

Emotional analysis is the technique that uses Natural Language Processing to automatically mine attitudes, opinions, perspectives, and emotions from text, audio, tweets, and database sources (NLP). In a sentiment analysis, views in a text are categorised into "positive," "negative," and "neutral" categories. Subjectivity analysis, opinion mining, and assessment extraction are other names for it.

Kajal et al [4] illustrated a cross cyber detection mechanism using monitored machine learning techniques with Project heuristic architecture of swarm intellect artificial bee hive with separate spectral transition and neural network with svm classifier as dual classification to create evaluation metrics to recognise internet backbone invaders. The accuracy rate of the DDoS attack-designed system is 98 percent, with an accuracy of 0.9[3].

Kushank et.al[5] Two gathering-based methodologies are used in this work. The first is reliant on logistic regression, k-nearest neighbour (KNN), and random forest, while the second is dependent on LSVM, and random forest. We have divided the material into three categories, such as Misogynist, Racist, and None, before using the procedures[6]. We discover that the second model had a better degree of precision than the other one we were using. The degree of accuracy that we obtained is 85%.

Khalid et.al[7]presented a variety of algorithms, including gradient boosting, decision trees, RF, and logistic regression. The technique used to show if the provided material is negative, positive, or neutral is narrative text.

Support Vector Machine (SVM), Naive Bayes (NB), and K-nearest neighbour are a few examples of classifier procedures that Meylan Wongkar et al illustrated for separating hate speech. Nave-Bayes had the highest level of precision (80%) compared to K nearest neighbours (75%), while K nearest neighbours had a greater level of accuracy than Support Vector Machine (63 percent). In the current article, we look at popular perceptions of the Republic of Indonesia's official candidate for the years 2019–24. For next work, we must analyse the current President's survey using a variety of internet media[8].

How to cope with identifying keywords on a Twitter account is suggested by Hajime Watanabe et al[9] . We must make use of the instances and unigram recognition that were afterwards learned from training sets. Violent, aggressive, or animosity-inducing language is a component of hate speech. We must verify the data from 2010 tweets, which reveals the accuracy of 78% of insulting tweets and the exactness of 87% of analyst tweets that are hostile or neutral. To identify the presence of hatred speech across diverse age, religion, gender, and other categories, we must do a quantitative and subjective analysis [10],

In their work, Dagar et al.[11] reported their attempt to assess several types of health-related tweets for depression and anxiety. We must identify the many types of emotions, such as negative.

Kshirsagar et al[12] use the LSTM ,GBDT and Word Embedding approach to identify hate speech on social media. The hate speech includes spreading false information, inciting violence, and other negative behaviours. The dataset was tested, and the findings showed an accuracy of 84% using a mixture of 90% receiving prepared information and 10% test data. Additional datasets must be tested exposed to the delayed effects of blended data in order to get amazing findings.

Numerous deep knowledge replicas, including support course machines, XGBoost, and additional ML methods, were detailed by Zamani et al[13] in their study. They dealt with datasets that were mixed-code Hindi-English and English-Hindi. The classifier's results favour Hindi and English in large part, with F scores of 55, 68, and 54 [14].

Kokatnoor et al. [15] A model called Stacked Weighted Ensemble is suggested for the identification of hate speech. Along with certain separate classifiers. Various tagged grouping approaches are used

http://dx.doi.org/10.36596/jcse.v3i2.533

for the order of emotions, such as joy, disgust, anger, and fear. After gathering information, classifiers provide results in the range of 80 to 92 percent Liu et al[16].

Hate keywords Fear, Disgust, and Anger were reported by [17]. as having a greater rate. 9984 positive, 34177 negative, and 4658 neutral terms were obtained from Twitter [18]. The larger percentage of unfavourable tweets demonstrates the type of content that is prevalent in online media. Future efforts should not only take into account a single attempt[19].

2. Method

The Data set used for the analysis is shown in table below which have 200000 rows and 3 columns as shown in Tabel 1 with the target, text and tweet as the header. The Process Flow chart is given in Fig 1 with the stages of import data, text cleaning, TF IDF vectorization, train test split, train and evaluate, adjust class imbalance, model evaluation, model building, regularization, hyperparameter tuning, get best parameter & evaluate and find recall and f1 score and top 10 terms used in the tweets is shown in Fig 2 Along with count of hate vs not hate speech used for sentiment analysis is shown in Fig 3.

Tabel 1. Dataset Used

	Target	Text	Tweet
0	0	At work a lot Of mail today also running late...	work mail today also run late still
1	0	@MissVix Aw.vwwh, you are indeed honoured! I	indeed honour admit slightly jealous right wan...
2	0	Why are chavs always sitting in the front of t...	chavs always sit front train want make
3	0	hi everyl my prom last omg it was amazin	every 1 prom last amazin love guna miss everl
4	0	@anoncel 1 want an cch0!	want echo
..	..		
199995	1	doesn't twitter anymore, but I will follow!	twitter anymore follow
199996	1	Goodmorning twitter people! Watching Goodmorni...	goodmorning twitter people watch goodmorning a...
199997	1	@yeevs just come join me. the one in Gardens.	come join garden come need good dose sweetness..
199998	1	@forty4vn ?) mua coi j t?	400gb thui
199999	1	thanks to Arthur i•ve never forgotten how to s...	thank arthur never forget spell aardvark

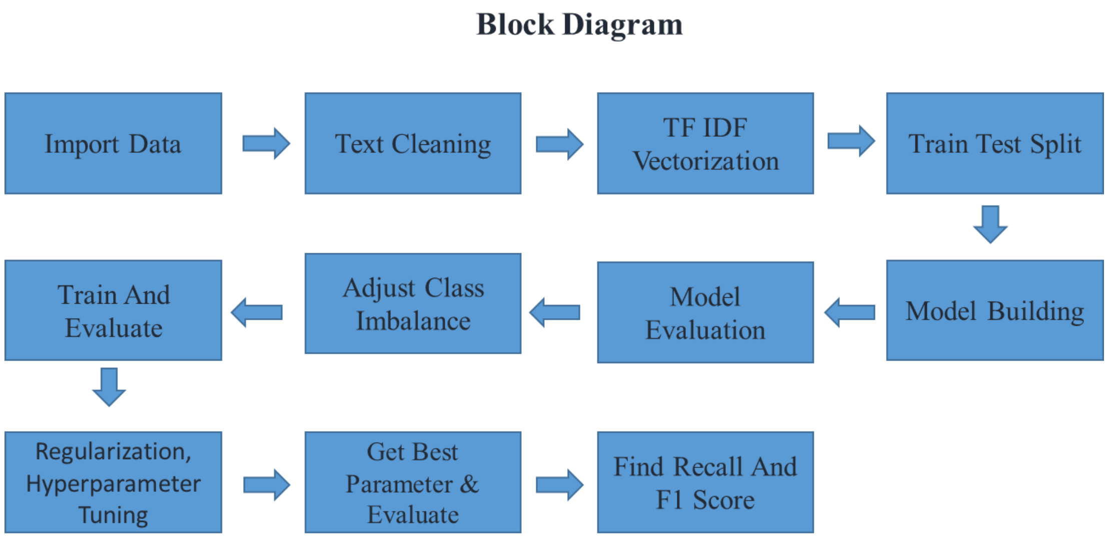

Fig 1. Flowchart of the process used

http://dx.doi.org/10.36596/jcse.v3i2.533

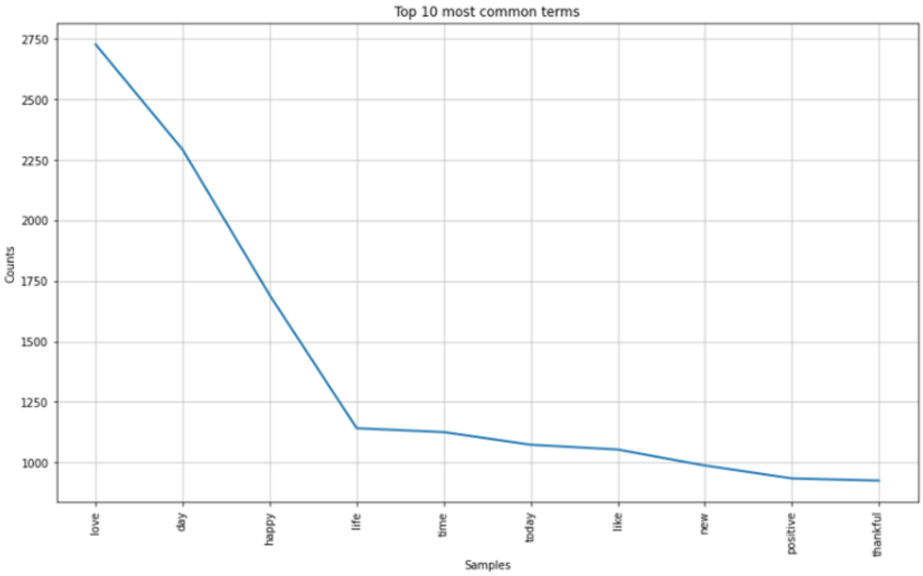

Fig 2. Top 10 Common terms used in the tweets

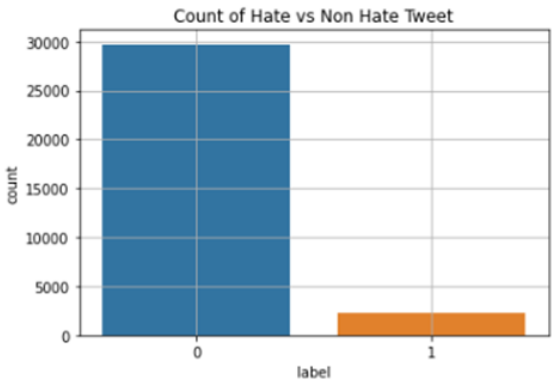

Fig 3. Count of Hate Vs Non Hate Tweets

3. Results and Discussion

3.1. AdaBoost Classifier

Any machine learning algorithm's performance may be improved with AdaBoost. When teaching weak learners, it works best. On a classification issue, these models produce accuracy that is just slightly better than random chance. Decision trees with one level are the method that works best with AdaBoost and is consequently used the most frequently. The AdaBoost algorithm, employed as an ensemble approach in machine learning, is known as adaptive boosting. The word "adaptive boosting" refers to the process of reassigning weights to each instance, with heavier weights being added to instances that were misclassified. In supervised learning, boosting is used to reduce bias and variance. It is founded on the idea that learners develop gradually. Each following student, with the exception of the first, is created from learners who have already been created. To put it another way, weak students become strong ones. Although the AdaBoost method functions similarly to boosting, there is a little difference in how it does so [20]. Fig 4 depicts the stacking strategy used in machine learning.

http://dx.doi.org/10.36596/jcse.v3i2.533

 e-ISSN 2721-0251

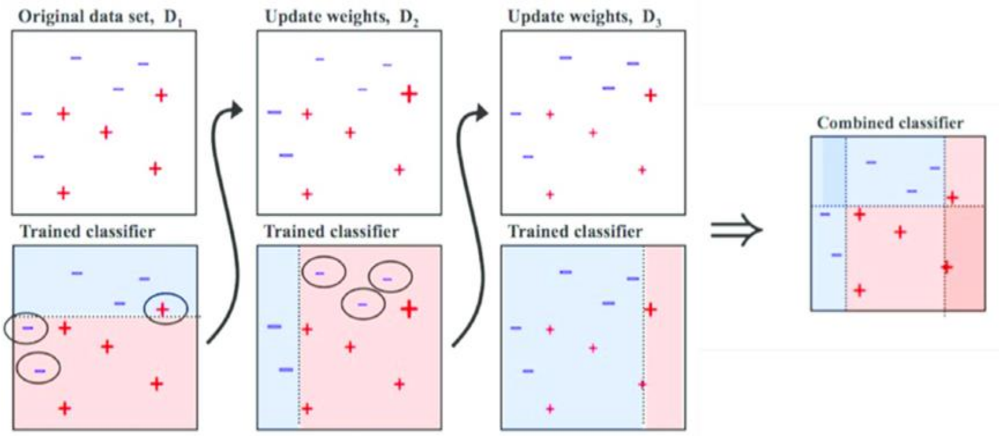

Fig 4. Adaboost approach used in Machine learning

3.2. Neural Net

An input vector is transformed into an output by layers of units (neurons) that make up a neural network. Each unit receives an input, processes it through a function, and then transfers the result to the following layer. In general, networks are characterised as being feed-forward, meaning that there is no feedback to the previous layer and each component feeds its production to all the components on the layer above it. Signals travelling from one unit to another are given weightings, and it is these allowances that are tweaked throughout the exercise phase to familiarize a neural net to the specific issue at hand [21].

Neural networks are influenced by the way that the human brain learns. It comprises of a manufactured set of parameters that allow the computer to learn and adjust by analysing new data. Each parameter is a function that, after receiving one or more inputs, also known as inputs or neurons, produces an output. These outputs are then sent on to the following brain layer, where they serve as inputs for their particular function. Once each neural layer has been assessed and the neuron's input has been received, the results are then transferred to the following layer of neurons[22]. Fig 5 displays a simple neural network. Also Different level of sentimental analysis are shown in Fig 6.

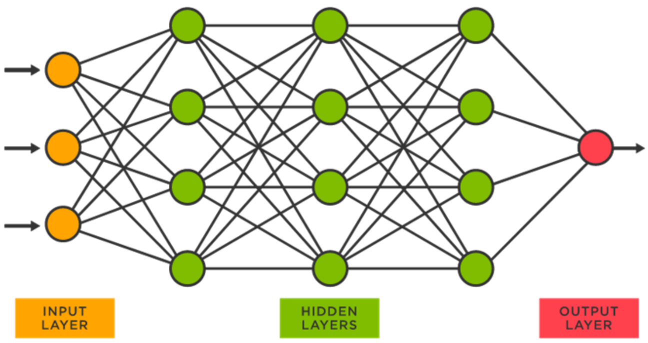

Fig 5. Simple Neural Net

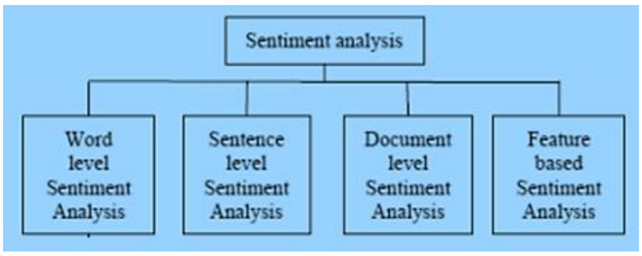

Fig 6. Different Levels of Sentiment analysis

http://dx.doi.org/10.36596/jcse.v3i2.533

3.4. Decision Tree Classifier

Decision tree classifiers have a wide range of effective applications. Their capacity to extract descriptive decisionmaking information from the provided data is their key strength[23]. Training sets can be used to create a decision tree.

The guided study algorithm family includes the decision tree approach. In contrast to other observed learning strategies, as seen in Fig 7, the decision tree method may be utilised to address problems like classification and regression.

Using predictions about the class or value of the destination variable, the Choice Tree aims to build an educational model that can be applied by students learning fundamental decision-making guidelines (training data) [24].

In decision trees, we anticipate a class label for a record from the hierarchy's root. We contrast the values of the best's quality with those of the root attribute. Based on a comparison, we leap to the next n and then follow the branch that corresponds to this number. Flow chart of Sentiment analysis tasks are given in Fig 8.

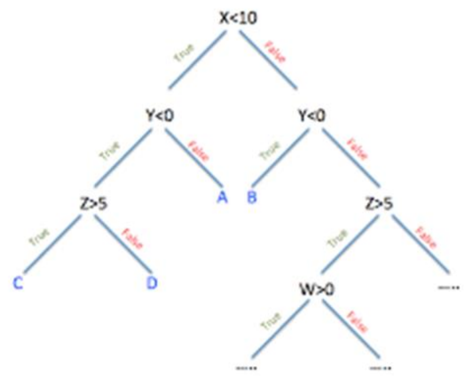

Fig 7. Working of DT

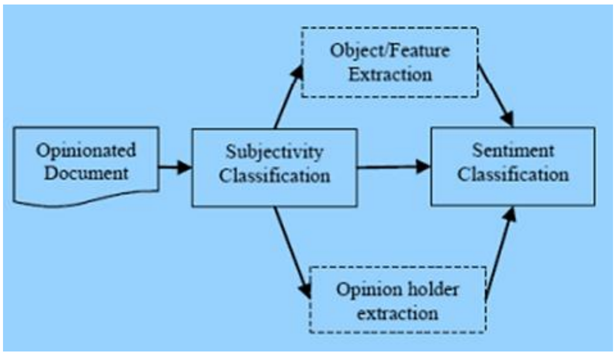

Fig 8. Flow chart of Sentiment analysis tasks

3.5. RBF SVM

A linear decision area also exists in the RBF kernel SVM decision region. The RBF Kernel SVM creates nonlinear combinations of your samples in a higher-dimensional space where you may make use of a linear boundary for your class-splitting decision:

Kernel functions like RBF are suggested for nonlinear datasets that are linear or otherwise inseparable. For a dataset that can be linearly separated, one may use the linear kernel function (kernel="linear") (linear dataset). You may train the optimal model using the SVM approach as illustrated in Fig 4 if you have a clear understanding of when kernel functions should be employed. A linear decision area also exists in the RBF kernel SVM decision region [25]. The RBF Kernel

http://dx.doi.org/10.36596/jcse.v3i2.533

SVM creates nonlinear combinations of your samples in a higher-dimensional space where you may make use of a linear boundary for your class-splitting decision:

Kernel functions like RBF are suggested for nonlinear datasets that are linear or otherwise inseparable. For a dataset that can be linearly separated, one may use the linear kernel function (kernel="linear") (linear dataset). You may train the optimal model using the SVM approach as illustrated in Fig 9 if you have a clear understanding of when kernel functions should be employed.

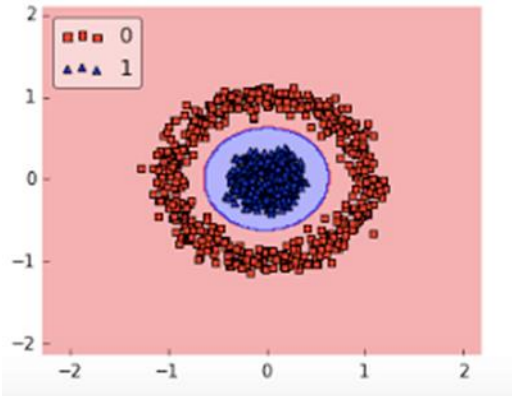

Fig 9. classification by RBF SVM

3.6. Nearest Neighbors Classifier

A machine learning technique called nearest neighbour classification seeks to categorise previously unobserved query items while differentiating between two or more destination classes. It is an example of supervised learning since, like any classifier, it needs some training data with predetermined labels [26].

K-Nearest Neighbors is a straightforward yet crucial machine learning classification method. It is a well-known supervised learning technique used in intrusion detection, data mining, and pattern identification.

Since it is non-parametric, or assumes no underlying assumptions about data distribution, it is broadly applicable in real-world situations.

Consider that there are two categories, A and B, and that we have a new data point, x1, and we are unsure which of the two categories this data point belongs to. To handle this kind of issue, a K-NN approach is necessary[27]. As seen in Fig 10, K-NN may be used to quickly identify the category or class of a certain dataset.

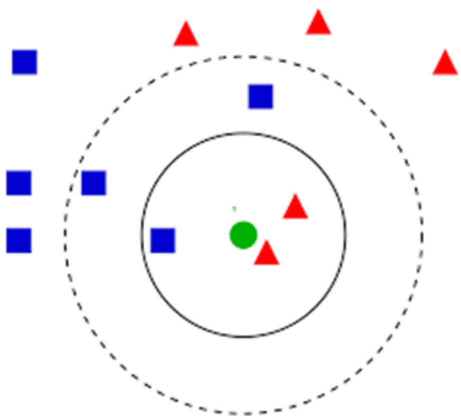

Fig 10. Nearest Neighbors Classifier

http://dx.doi.org/10.36596/jcse.v3i2.533

3.7. Random Forest Classifier

A well-known machine learning algorithm Random Forest is a technique used in the supervised learning process. It may be used to solve ML problems requiring both classification and regression. It is based on the concept of ensemble learning, which is a way of combining several classifiers to handle complex problems and improve model performance[28].

Rf is a classifier that, as the name indicates, utilises a number of decision trees on different sets of the input dataset and combines them to improve the dataset's prediction accuracy. Rather of relying on a single decision tree, the random forest uses predictions from each tree to estimate the plurality of predictions' amount of votes [29].

Even without adjusting the hyperparameters, random forest is a flexible and simple strategy that produces excellent results. Due to its ease and variety, it is also one of the greatest often rummage-sale procedures. To provide a additional accurate and reliable forecast, random forests create and combine many decision trees [30].

Given that organization and reversion glitches make up the mainstream of modern machine learning schemes, the chance forests offer a significant advantage in many applications. Because classification is frequently seen as the machine's foundation, let's examine how random forests classify data. Fig 11 shows how two trees appear to be a random forest from below.

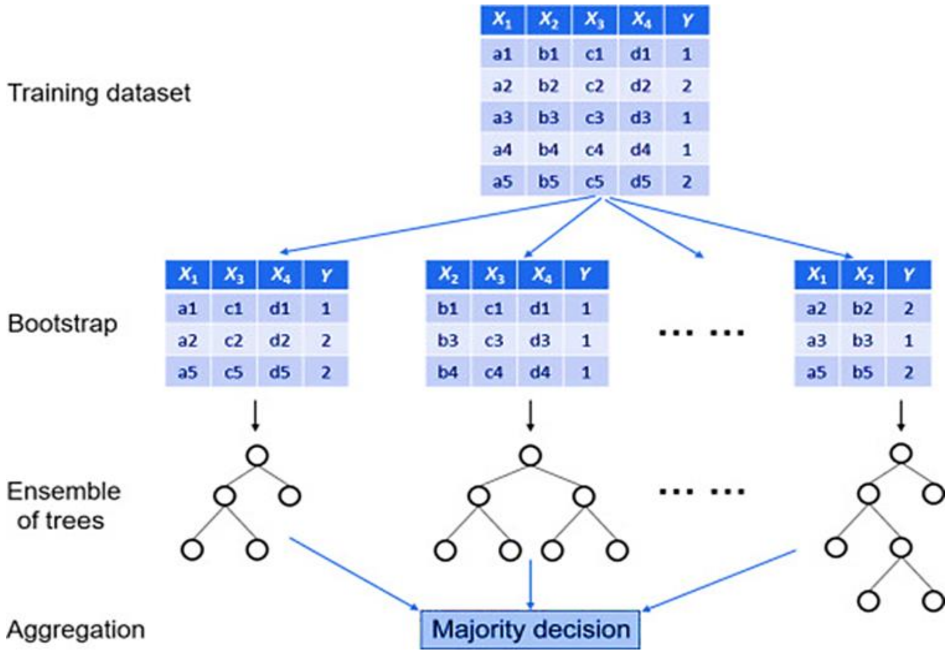

Fig 11. Random Forest Process

As trees grow, the random forest model becomes more unpredictable. Instead than focusing on the primary feature when dividing a node, it considers a random assortment of features. This results in a wide range, which frequently results in a better model [31].

3.8. Ludwig Classifier

Without creating a single line of code, models may be predicted and utilised using Ludwig, a powerful learning toolset. It is developed on top of TensorFlow and makes use of an abstraction based on data types to build a large number of applications. Ludwig's declarative file format enables extremely speedy prototype and model iteration. It allows experienced users to be much more productive by speeding up tasks that would otherwise take months or minutes. It is suitable for novices to train profound learning models without knowing all TensorFlow intricacies or profound learning in general [32].

http://dx.doi.org/10.36596/jcse.v3i2.533

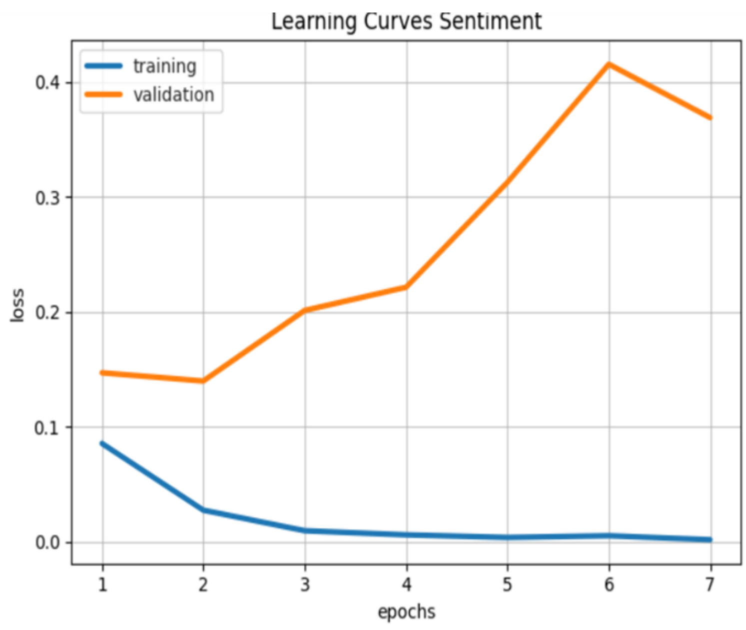

Fig 12. Learning Curve Sentiment

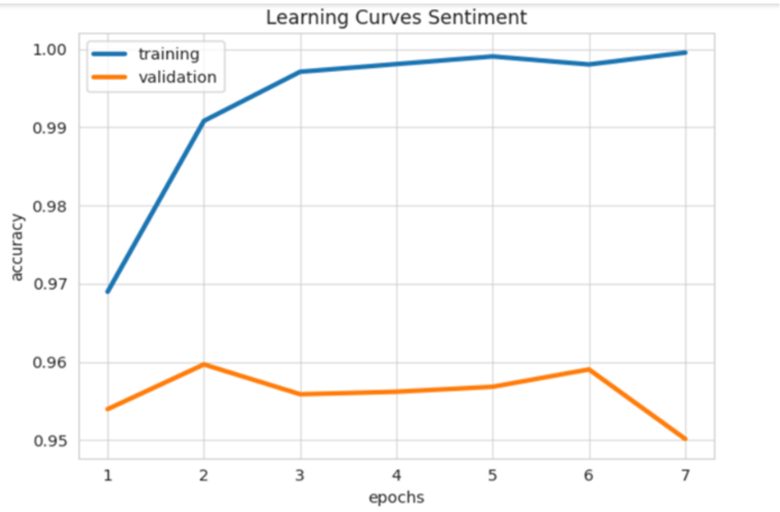

Fig 13. Learning Curve using Ludwig Classifier

A very excellent indication at 7 epochs, the learning curve obtained using deep learning guarantees about 99.9% accuracy. Fig 12 loss vs. epoch curve illustrates how a loss in the training curve decreases to virtually zero with a rise in epoch, which in and of itself demonstrates the system's accuracy. Fig 13 makes it quite evident that using the Ludwig classifier with many epochs boosts accuracy.

Based on the pre-processed data sets, a number of Classification techniques were developed in the Python programming language on Google Colab. These methods included Boosting, Logistic Regression, SVM, and Naive Bayes. The top 8 algorithms' conclusions show positive outcomes for the situation. On the clean data set, our classifier was trained using the default functionality. Precision, F1-score, recall, accuracy, and ROC area were the four metrics used for assessment. A crucial confusion matrix is a 2-dimensional matrix that offers details about the actual classes and anticipated classes of a classifier. Model summary is Shown in Table 2.

http://dx.doi.org/10.36596/jcse.v3i2.533

Table 2. Model Summary

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 30)]              0
_________________________________________________________________
embedding (Embedding)        (None, 30, 300)           20047200
_________________________________________________________________
dropout (Dropout)            (None, 30, 300)           0
_________________________________________________________________
conv1d (Conv1D)              (None, 24, 128)           268928
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 18, 128)           114816
_________________________________________________________________
global_max_pooling1d (Global (None, 128)               0
_________________________________________________________________
dense (Dense)                (None, 512)               66048
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
```

The various results are combined and shown in Table 3

Table 3. Comparison among different classifiers

Algorithm used	Precision	Recall	f1-score	Accuracy
Linear SVM	1	0.93	0.96	0.93
Nearest Neighbors	0.99	0.94	0.96	0.93
Random Forest	0.97	0.96	0.97	0.96
Linear SVC	0.97	0.96	0.97	0.96
AdaBoost	0.97	0.94	0.95	0.94
Neural Net	1	0.93	0.96	0.92
Decision Tree	0.95	0.94	0.94	0.94
RBF SVM	0.95	0.96	0.96	0.95

Inference from table 3

1. Neural Net and Linear SVM are discovered to have the maximum value for accuracy, which is unity. Except for the Decision Tree, all other classifiers have a score over 0.95.
2. Recall indicates how accurately a classifier can predict future events. It reaches its maximum in RBF SVM, Random Forest, and Linear SVC, and it is more than 0.93 in all other cases, indicating how accurate the prediction is.
3. The F1 Score, which is the harmonic average of accuracy and recall, has a maximum in both Random Forest and Linear SVC and virtually similar value.
4. One of the key metrics for any machine learning application is accuracy, which is the percentage of correctly categorised predictions. In this study, the maximum accuracy for Random Forest and Linear SVC was determined to be around 97 percent. Additionally, it is discovered that employing a deep learning model with Ludwig Classifier, as illustrated in Fig 14, an accuracy of roughly around 99.9 percent is attained.

http://dx.doi.org/10.36596/jcse.v3i2.533

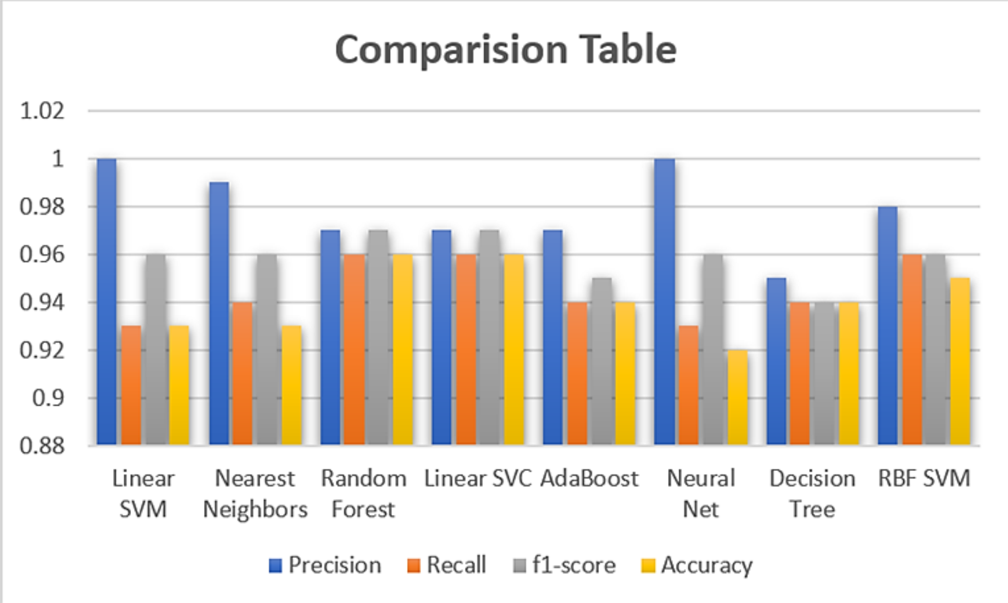

Fig 14. Summary of different classifiers

4. Conclusion

In this study, we have effectively used deep learning and a variety of categorization techniques to predict human behaviour. Performance metrics including accuracy, recall, precision, and f1-score were obtained during the study, which was done in Python. The results show that Random Forest and Linear SVC have maximum accuracy of about 97 percent. A deep learning network using Ludwig Classifier also achieves an accuracy of nearly 99.9%, as shown in Fig 9. Researchers in the same field will find this study article useful.

References

[1] V. Sundararaj and M. Rejeesh, "A detailed behavioral analysis on consumer and customer changing behavior with respect to social networking sites", Journal of Retailing and Consumer Services, vol. 58, p. 102190, 2021. https://doi.org/10.1016/j.jretconser.2020.102190

[2] Sultan, M.T.; Sharmin, F.; Badulescu, A.; Gavrilut, D.; Xue, K. Social Media-Based Content towards Image Formation: A New Approach to the Selection of Sustainable Destinations. Sustainability 2021, 13, 4241. https://doi.org/10.3390/su13084241

[3] Salminen J, Mustak M, Corporan J, Jung S, Jansen BJ. Detecting Pain Points from User-Generated Social Media Posts Using Machine Learning. Journal of Interactive Marketing. 2022;57(3):517-539. https://doi:10.1177/10949968221095556

[4] Zhang, T., Schoene, A.M., Ji, S. et al. Natural language processing applied to mental illness detection: a narrative review. npj Digit. Med. 5, 46 (2022). https://doi.org/10.1038/s41746-022-00589-7

[5] Q. Pham et al., "Swarm intelligence for next-generation networks: Recent advances and applications", Journal of Network and Computer Applications, vol. 191, p. 103141, 2021. https://doi.org/10.1016/j.jnca.2021.103141

[6] Hashemi, Mohammad J. Detecting Anomalies in Network Systems by Leveraging Neural Networks. University of Colorado at Boulder ProQuest Dissertations Publishing, 2021. 28652078.

[7] Gaur, V., Kumar, R. Analysis of Machine Learning Classifiers for Early Detection of DDoS Attacks on IoT Devices. Arab J Sci Eng 47, 1353–1374 (2022). https://doi.org/10.1007/s13369-021-05947-3

[8] M. R. Romadhon and F. Kurniawan, "A Comparison of Naive Bayes Methods, Logistic Regression and KNN for Predicting Healing of Covid-19 Patients in Indonesia," 2021 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT), 2021, pp. 41-44, https://doi.org/10.1109/EIConCIT50028.2021.9431845

[9] J. Sachdeva, K. K. Chaudhary, H. Madaan and P. Meel, "Text Based Hate-Speech Analysis," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), 2021, pp. 661-668, https://doi.org/10.1109/ICAIS50930.2021.9396013

http://dx.doi.org/10.36596/jcse.v3i2.533

[10] Q. Pham et al., "Swarm intelligence for next-generation networks: Recent advances and applications", Journal of Network and Computer Applications, vol. 191, p. 103141, 2021. https://doi.org/10.1016/j.jnca.2021.103141
[11] M. Wongkar and A. Angdresey, "Sentiment Analysis Using Naive Bayes Algorithm Of The Data Crawler: Twitter", 2019 Fourth International Conference on Informatics and Computing (ICIC), 2019.
[12] Rajput, G., Punn, N.S., Sonbhadra, S.K., Agarwal, S. Hate Speech Detection Using Static BERT Embeddings. In: Srirama, S.N., Lin, J.CW., Bhatnagar, R., Agarwal, S., Reddy, P.K. (eds) Big Data Analytics. BDA 2021. Lecture Notes in Computer Science(), vol 13147. 2021. Springer, Cham. https://doi.org/10.1007/978-3-030-93620-4_6
[13] G. Liu, S. Wang, B. Wan, Z. Wang and C. Wang, "ML-Stealer: Stealing Prediction Functionality of Machine Learning Models with Mere Black-Box Access," 2021 IEEE 20th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), 2021, pp. 532-539, https://doi.org/10.1109/TrustCom53373.2021.00083
[14] M. Dagar, A. Kajal and P. Bhatia, "Twitter Sentiment Analysis using Supervised Machine Learning Techniques," 2021 5th International Conference on Information Systems and Computer Networks (ISCON), 2021, pp. 1-7, https://doi.org/10.1109/ISCON52037.2021.9702333
[15] Aljero MKA, Dimililer N. A Novel Stacked Ensemble for Hate Speech Recognition. Applied Sciences. 2021; 11(24):11684. https://doi.org/10.3390/app112411684
[16] Ankita, S. Rani, A. Bashir, A. Alhudhaif, D. Koundal and E. Gunduz, "An efficient CNN-LSTM model for sentiment detection in #BlackLivesMatter", Expert Systems with Applications, vol. 193, p. 116256, 2022. https://doi.org/10.1016/j.eswa.2021.116256
[17] Madukwe, K.J., Gao, X., Xue, B. What Emotion Is Hate? Incorporating Emotion Information into the Hate Speech Detection Task. In: Pham, D.N., Theeramunkong, T., Governatori, G., Liu, F. (eds) PRICAI 2021: Trends in Artificial Intelligence. PRICAI 2021. Lecture Notes in Computer Science(), vol 13032. 2021. Springer, Cham. https://doi.org/10.1007/978-3-030-89363-7_21
[18] Ankita, S. Rani, A. Bashir, A. Alhudhaif, D. Koundal and E. Gunduz, "An efficient CNN-LSTM model for sentiment detection in #BlackLivesMatter", Expert Systems with Applications, vol. 193, p. 116256, 2022. https://doi.org/10.1016/j.eswa.2021.116256
[19] I. Anderson and W. Wood, "Habits and the electronic herd: The psychology behind social media's successes and failures", Consumer Psychology Review, vol. 4, no. 1, pp. 83-99, 2020. https://doi.org/10.1002/arcp.1063
[20] H. Sihotang, M. Zarlis, S. Efendi, D. Jollyta and Husain, "Evaluation of Maturity Level of Information and Communication Technology (ICT) Governance with CobIT 5.0 Case Study: STMIK Pelita Nusantara Medan", Journal of Physics: Conference Series, vol. 1255, no. 1, p. 012046, 2019. https://doi.org/10.1088/1742-6596/1255/1/012046
[21] V. Rybalkin, N. Wehn, M. R. Yousefi and D. Stricker, "Hardware architecture of Bidirectional Long Short-Term Memory Neural Network for Optical Character Recognition," Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017, pp. 1390-1395, https://doi.org/10.23919/DATE.2017.7927210
[22] C. Aggarwal, "Neural Networks and Deep Learning", 2018. https://doi.org/10.1007/978-3-319-94463-0
[23] Polat, Kemal, and Salih Güneş. "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform." Applied Mathematics and Computation 187, no. 2 (2007): 1017-1026. https://doi.org/10.1016/j.amc.2006.09.022
[24] Mueen A, Zafar B, Manzoor U. Modeling and Predicting Students' Academic Performance Using Data Mining Techniques. International journal of modern education & computer science. 2016 Nov 1;8(11). https://doi.org/10.5815/ijmecs.2016.11.0
[25] Fouad IA. A robust and efficient EEG-based drowsiness detection system using different machine learning algorithms. Ain Shams Engineering Journal. 2022 Aug 1:101895. https://doi.org/10.1016/j.asej.2022.101895
[26] A. L. Buczak and E. Guven, "A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection," in IEEE Communications Surveys & Tutorials, vol. 18, no. 2, pp. 1153-1176, Secondquarter 2016, https://doi.org/10.1109/COMST.2015.2494502
[27] Schulte, Matthias, and Katharina Morik. "Real-time feature extraction from video stream data for stream segmentation and tagging." an der Technischen Universit¨at Dortmund Fakult¨at f¨ur Informatik, Dortmund, January 22, 2013.
[28] Osisanwo FY, Akinsola JE, Awodele O, Hinmikaiye JO, Olakanmi O, Akinjobi J. Supervised machine learning algorithms: classification and comparison. International Journal of Computer Trends and Technology (IJCTT). 2017 Jun;48(3):128-38.

http://dx.doi.org/10.36596/jcse.v3i2.533

[29] Dev VA, Eden MR. Formation lithology classification using scalable gradient boosted decision trees. Computers & Chemical Engineering. 2019 Sep 2;128:392-404.
[30] Dev VA, Eden MR. Formation lithology classification using scalable gradient boosted decision trees. Computers & Chemical Engineering. 2019 Sep 2;128:392-404.
[31] Abidi SM, Xu Y, Ni J, Wang X, Zhang W. Popularity prediction of movies: from statistical modeling to machine learning techniques. Multimedia Tools and Applications. 2020 Dec;79(47):35583-617. https://doi.org/10.1007/s11042-019-08546-5
[32] Jupalle H, Kouser S, Bhatia AB, Alam N, Nadikattu RR, Whig P. Automation of human behaviors and its prediction using machine learning. Microsystem Technologies. 2022 Aug;28(8):1879-87. https://doi.org/10.1007/s00542-022-05326-4