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# Accuracy Enhancement During Sentiment Analysis in Twitter Using CNN

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***Abstract*— In order to determine user sentiment, researchers are utilizing sentiment analysis on a Twitter data set that includes both graphical and textual user comments. The world is fast changing as a result of contemporary technological breakthroughs. In today's world, the Internet has become a need for everyone. People are using social network applications to voice their opinions on common issues because of the rapid rise of these platforms. Obtaining and analyzing people's answers to purchasing a product, utilizing public services, and so on is essential. Opinion mining (also known as sentiment analysis) is a common practice for getting ready for a discussion in which the sentiments that underlie various points of view are sought to be discovered. Recent years have seen the rise of sentiment analysis as a tool for determining how consumers are feeling. Textual and graphical tweets posted by users are the primary focus of current study. CNN-based technique is used for graphical content; neural networks are used for textual content. An increasing amount of attention has been paid in recent years to "tweets" (comments) and the content of these expressions in opinion research utilizing Twitter data. Because of this, the goal of this research is to find out how various sentiment analyses on Twitter data turn out. The suggested research uses a neural network machine learning method to detect feelings based on graphical input.**

***Keywords*—Twitter data, Opinion mining, Sentiment analysis, Machine learning, CNN**

## I. INTRODUCTION

Consumer resources, such as internet and social media, reviews and survey responses, and health materials, can all benefit from SA in a variety of settings, from marketing to customer service to medicine. Use of SA on Twitter is currently being studied. Textual and artificial neural network and CNN mechanisms are used to categories the graphical information in this research. The data gathering would be divided into two parts. The neural network approach might be used to train text to provide a more accurate answer. Graphical content is taught using CNNs in order to anticipate. Data from frequent users is taken into account while doing sentimental analysis. The suggested technique aims to solve the issues that previous researchers ran across while trying to analyze sentiment. As a result of the simulation effort, a sentiment analysis technique for textual and visual Twitter data has been developed. The simulation results have shown that the suggested work is capable of providing a more accurate and dependable answer than the current method. Text mining is becoming increasingly popular with the use of product reviews that incorporate feelings. Various computer linguistics experiments are also examined. The focus of the research is on the correlation between tweets and data from Twitter. It was taken into account how customers rated the items. Researchers looked on Deep Neural Networks and Recurring Neural Networks (RNN). Research should yield a better response for sentiment analysis.

### *A. CNN*

In image identification and processing, a CNN is a sort of artificial neural network designed to handle pixel input. Neural network "layers" are rows of data items that are all hosted by the same neurons. In CNN, there are no neurons or weights. CNN, on the other hand, applies many filters and layers to photos before analysing the results. Image categorization and identification is facilitated by CNNs because to their high level of accuracy. By first forming a network in a hierarchical fashion, like a funnel, the CNN is able to produce a fully-connected layer in which all neurons are coupled to each other and the processed output is stored.

### *B. SENTIMENT ANALYSIS*

Affective states and subjective information may be systematically detected, extracted, measured, & analysed via the use of NLP, text analysis, computational linguistics, and biometrics.Sentiment analysis is frequently used in a variety of contexts, including marketing, customer service, and clinical medicines, to better understand how customers feel about products and services.

### *C. SENTIMENT ANALYSIS APPROACH FOR PREDICTION*

There has been a rise in recent years in research efforts connected to emotions in written and graphical materials. This is not surprising. It's becoming more common to see studies on sentiment analysis published in the last year. The findings of these studies have been included into the current inquiry. Sentiment analysis is a subtopic that certain researchers are interested in exploring. Opinion mining is another term for what we're doing here. It's been presented as a collection of text and graphics. People's thoughts and feelings are taken into account in these studies. There are also considerations given to the many aspects of the issues, personalities, events, and concepts. The types of applications that may be created employing such an idea are numerous. The proliferation of websites makes it challenging to track down and analyse online thought hubs and distil the information they supply. In extended forum discussions and blogs, there is often a lot of opinionated language and visuals that are difficult to interpret.

## II. LITERATURE REVIEW

There are already academic publications on topics like product reviews, sentiment analysis, and opinion mining. Ronan Collobert [1] et al.have using CNN The author shows how several tasks, such as POS tagging, chunking, named

entity identification, and semantic role labeling, may be accomplished using a single neural network and learning algorithm.

Dave [2] did product reviews were being analyzed with the purpose of extracting and classifying user opinions. For feature extraction and scoring, the classifier uses information retrieval techniques, and the results vary depending on the testing circumstance. Traditional machine learning isn't the only option when it comes to finding new ways to learn. Due to the noise and ambiguity of online search results, it was difficult to conduct operations on individual phrases.

Maria Soledad Elli [3] did sentiment derived by reading customer reviews. They've studied the data and used it to create a business plan. The author argues that the technology he describes was more accurate. Multinomial Naive Bayesian has been used by researchers. Classifiers are at work here. Vector machines are supported by mechanisms as well. Fake review identification and trend patterns were also detected using ML techniques.

S. Hota and S. Pathak[4] did multi-category Twitter sentiment analysis using a KNN classifier In common parlance, a person's "sentiment" referred to their own personal emotional condition. By sifting through user-generated material including blog posts, tweets, status updates, and reviews, sentiment analysis is a subset of data mining that analyses online user responses to events, organisations, products, brands, and other identifiers. In this research, they classify sentiments according to a variety of distinct dimensions. Using the conventional evaluation parameters, the new strategy outperforms the current method.

B. Liu and L. Zhang [5] did surveys using analysis of Sentiment and Opinion Mining. Opinion mining, also known as sentiment analysis, was the computational examination of people's opinions and sentiments about a wide range of things, including specific persons, places, events, topics, and characteristics.

Callen Rain [6] looked extensive work on natural language processing theory and theory. A review has been categorized using these methods. It's possible that these are favourable or negative comments. Deep-learning neural networks are being used in research. Neural networks have become a popular tool for sentiment analysis. Shoppers on Amazon were urged to provide feedback on the products they purchased.

R. Socher [7] proposed recursive neural networks are being used so that problems like sentiment detection may be better understood in terms of compositionality. This study will make use of both KNN, and SVM, and cutting-edge DL strategies.

Xu Yun et al [8] by used methods already in use, such as Stanford University's perceptron, naive bayes, and SVM. Cross-validation was performed on 70% of the total data.

KumarRavi, VadlamaniRavi [9] did review of tasks, methods, and uses for opinion mining and sentiment analysis.. The publication also includes a summary table of more than 100 papers, as well as a list of open issues.

Zainuddin [10] proposed In 2017, Twitter users' ambivalent emotions were sorted using an aspect-based sentiment analysis. In this research, Twitter sentiment analysis was broken down into its component parts to reveal previously hidden insights. We describe an unique hybrid sentiment classification approach for Twitter that makes use of a feature selection mechanism.

M. Z. Asghar [11] proposed Using a hybrid classification technique for Twitter sentiment analysis. Classifying tweets with a hybrid classification technique was the topic of this research, which attempts to address these challenges.

Alsaeedi, Abdullah & Khan, Mohammad [12] in 2019, did examination of Twitter data sentiment analysis techniques. They believed that the world is rapidly changing as a result of current technological advancements.

Shathik, Anvar [13] proposed machine learning techniques for sentiment analysis.

TABLE I. EXISTING RESEARCHES

| Sno. | Author / Year | Objective of research | Methodology | Limitation |
|---|---|---|---|---|
| 9. | Kumar Raviab, VadlamaniRavia /2015 | An investigation of the tasks, methods, and applications of sentiment analysis and opinion mining | Sentiment analysis | Need to integrate intelligent model. |
| 10 | N. Zainuddin/2017 | Twitter aspect-based sentiment analysis for hybrid sentiment categorization | Sentiment analysis | Need to use neural network for more accurate result. |
| 11 | M. Z. Asghar/ 2018 | TSAF with hybrid classification | Sentiment analysis | Scope of research is limited. |
| 12 | Alsaeedi, Abdullah & Khan, Mohammad /2019 | A Study of Twitter Data Sentiment Analysis Methods | Sentiment analysis | There is lack of technical work. |
| 13 | Shathik, Anvar & Karani, Krishna Prasad/ 2020 | Sentiment Analysis Applied to Machine Learning Techniques: A Literature Review | Sentiment analysis using machine learning | Research is just a review no practical solution found. |
| 14 | Liu, H., & Cocea, M. /2017 | Fuzzy rule-based systems that can be used to interpret sentiment | Sentiment analysis | Need to introduce machine learning approach |
| 15 | Abo, M./2018 | Algorithms for sentiment analysis: Arabic and English language performance | Sentiment analysis | Scope of research is limited to Arabic and English |
| 16 | Bansal/ 2019 | A Supervised Learning Approach for a Sentimental Analysis of YouTube Data | Sentiment analysis | The performance is very slow |

| | | | | |
|---|---|---|---|---|
| 17 | Alsaeedi/2019 | A Study of Twitter Data Sentiment Analysis Methods | Sentiment analysis | There is lack of technical implementation. |
| 18 | Sadhasivam/2019 | Ensemble ML Algorithm for Amazon Product Sentiment Analysis | Sentiment analysis using machine learning | System is required to be more fast. |
| 19 | Hasan/2018 | Sentimental Analysis of Twitter Accounts Using ML | Sentiment analysis using machine learning | There is need to improve the accuracy during decision making. |
| 20 | Sultana/2019 | Positive and Negative Affective Analysis | Sentiment Analysis | Scope of research is limited. |
| 21 | Raza, H./2019 | Sentiment Analysis in Scientific Texts using ML | Sentiment Analysis using Machine Learning | Need to improve accuracy and performance. |
| 22 | Valencia, F./2019 | Sentiment Analysis and ML Predict Cryptocurrency Price Movement | Sentiment Analysis and Machine Learning | Research is not considering areas other than cryptocurrencies. |
| 23 | Daeli/2020 | Information Gain and K-Nearest Neighbor Sentiment Analysis for Movie Review Sentiment Analysis | Sentiment Analysis | There is need to introduce optimization mechanism. |
| 24 | Kumar, S/2020 | Sentiment analysis and ML : a study of the effects of age and gender. | Sentiment Analysis and Machine Learning | Research work is limited to gender based sentiment analysis. |
| 25 | Shuhidan, S. M./2018 | ML Algorithm Sentiment Analysis of Financial News Headlines | Sentiment Analysis and Machine Learning | Work is limited to financial news. |

## III. PROBLEM STATEMENT

Researchers have already presented an approach that takes use of a bare minimum of characteristics in their previous work. In order to categorize tweets, they looked at their content. They also investigate the relevance of automatically identifying ironic tweets. They've shown how to improve the accuracy of sentiment analysis. Reviewing phones, politics, sports, movies, and other electrical gadgets were among the themes that were considered for inclusion in the collection. They used three different algorithms and got an accuracy of above 80%. When compared to Naive Bayes & Maximum Entropy, SVM provides better accuracy. However, SVM is not without its flaws.

1. On data that is heavily skewed or unbalanced, SVMs perform poorly.
2. Even if you have several classes, you shouldn't use SVMs.
3. SVMs are ineffective when the number of features exceeds the number of training samples.
4. SVMs are not a suitable choice for incremental learning if your data sets arrive in batches and each time you wish to update your learning model.
5. SVMs aren't ideal if you need to train many datasets at the same time.

## IV. RESEARCH METHODOLOGY

In the sections that follow, we'll go through some of the ways in which you may put this research to use.

i. Inquiry-based research, which aims to discover new issues and provide solutions.

ii. Constructive Research, which focuses on finding answers to a specific problem.

iii. Empirical research is used to determine whether or not a proposed solution is feasible based on available data.

Facts from Twitter are preprocessed in order to retrieve the most important data. Consider the following collection of data, on which the predicted results are to be based. Afterwards, this data is categorized based on the content of its text and graphics. The CNN model is used to learn graphical content. To conclude, the current model's accuracy and performance are compared to previous models.

TABLE II. COMPARISON OF PREVIOUS AND PROPOSED WORK

| | **Previous research [4]** | **Proposed work** |
|---|---|---|
| Preprocessing | Not applicable | Performed to eliminate useless content to increase accuracy and performance |
| Data classification | Not applicable | Data is classified to textual and graphical contents |
| Scope | Limited | Wide |
| Training model used | CNN | Hybrid CNN |
| Performance | Comparatively slow | Comparatively high |
| Data set | Tweets of users | Tweets of users |

## V. RESULT AND DISCUSSION

Simulated user tweets are being used to determine product sentiment in the simulation for focus. Simulated tweets from Twitter were retrieved and categorised in text and visual sections during phase 1 of the experiment. In phase 2, the ANN technique was used to train text material, while the CNN approach was used to learn visual content. Phase 3 involves the separation of training and testing datasets. During Phases 4 and 5, text preparation and converting a document to a sequence are the primary goals. Create and train ANN and CNN networks in phase 6. Phase 8 concludes with testing on a network that has been trained.

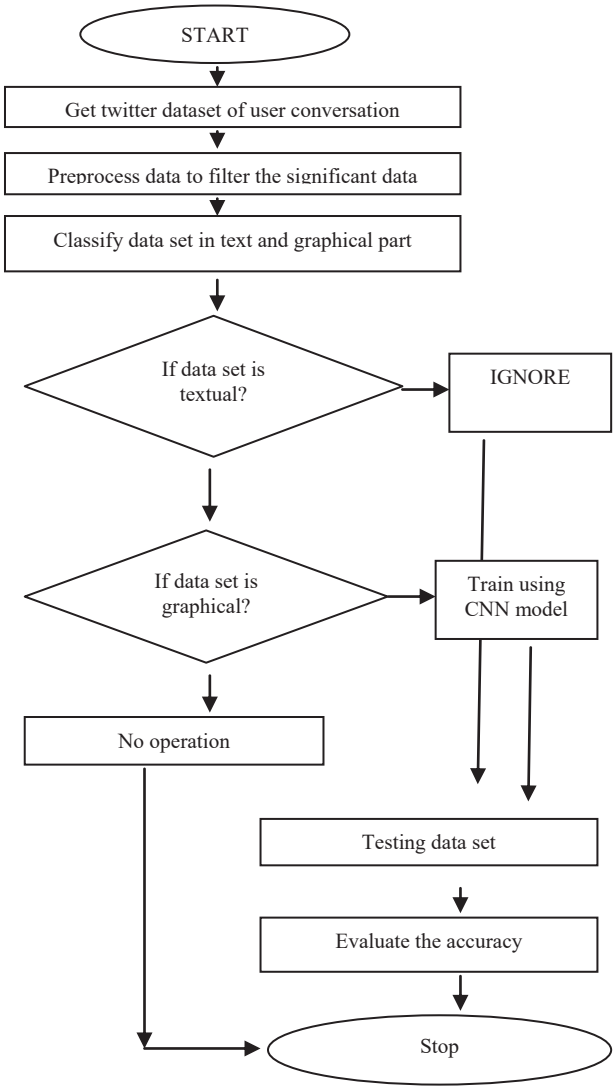


Fig. 1. Flow chart of proposed work

**Phase 1:** Get the data

a. Data from a Twitter account
b. This set of data includes both text and graphics.

**Phase 2 :** Data classification

a. Classify a variety of data types, including text and graphics.
b. Input the graphics dataset and use it to train your CNN model

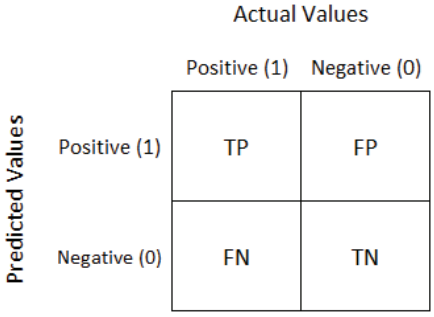


Fig. 2. Confusion matrix

## VI. TESTING PHASE

Dataset of textual and graphical content has been extracted from live tweeter handle of "ELON MUSK". This twitter handle has 60.7 M followers. Regular posts related to new innovations and cryptocurrency are posted here. The textual and graphical tweets have been on considered. Then trained CNN network considers 6000 images while ANN considers 30000 records for training. Research work has considered 1900 image from tweets and 10000 records from textual records. 1900 images have been passed for testing to CNN based training model to test accuracy. In similar fashion 10000 records have been passed in ANN to detect the sentiment of users.

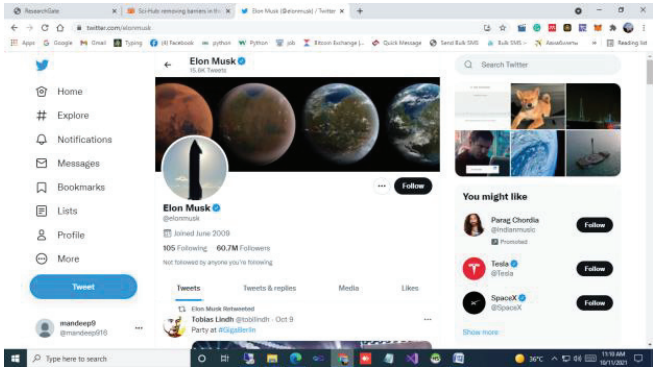


Fig. 3. Twitter handle of Elon Musk

### *A. Simulation for Graphical Contents*

Graphical content considers the following type of feed backs from users. These images are consisting some of the images that are presenting normal status of user, some are presenting joy status, some are presenting sad, some are annoying, and some are showing happiness. CNN model would be made in order to predict the sentiment of users considering there feed backs on different tweets.

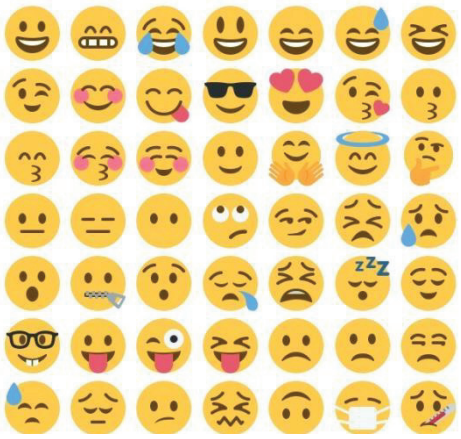

Fig. 4. Images presenting the sentiment of users

In present dataset 301 images expression present joy, 402 presents happy status, 638 shows normal status, 275 shows sad status while 284 showed annoyed status.

Training and testing of graphical content using CNN model without preprocessing has provided following confusion matrix:

TABLE III. CONFUSION MATRIX FOR PREVIOUS WORK

| | Joy | Happy | Normal | Sad | Annoyed |
|---|---|---|---|---|---|
| **Joy** | 275 | 6 | 9 | 9 | 2 |
| **Happy** | 3 | 379 | 8 | 5 | 7 |
| **Normal** | 5 | 4 | 609 | 8 | 12 |
| **Sad** | 4 | 9 | 7 | 251 | 4 |
| **Annoyed** | 3 | 5 | 7 | 5 | 264 |

### *B. Results*

TP: 1778
Overall Accuracy: 93.58%

TABLE IV. ACCURACY CHART FOR PREVIOUS WORK

| Class | n (truth) | n (classified) | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|---|
| **1** | 290 | 301 | 97.84% | 0.91 | 0.95 | 0.93 |
| **2** | 403 | 402 | 97.53% | 0.94 | 0.94 | 0.94 |
| **3** | 640 | 638 | 96.84% | 0.95 | 0.95 | 0.95 |
| **4** | 278 | 275 | 97.32% | 0.91 | 0.90 | 0.91 |
| **5** | 289 | 284 | 97.63% | 0.93 | 0.91 | 0.92 |

Training and testing of graphical content using CNN model after preprocessing has provided following confusion matrix:

TABLE V. CONFUSION MATRIX FOR PROPOSED WORK

| | Joy | Happy | Normal | Sad | Annoyed |
|---|---|---|---|---|---|
| **Joy** | **294** | **2** | **4** | **1** | **0** |
| **Happy** | **3** | **385** | **5** | **4** | **5** |
| **Normal** | **7** | **5** | **623** | **2** | **1** |
| **Sad** | **4** | **4** | **6** | **253** | **8** |
| **Annoyed** | **3** | **3** | **5** | **4** | **269** |

### *C. Result*

TP: 1824
Overall Accuracy: 96%

TABLE VI. ACCURACY CHART FOR PROPOSED WORK

| Class | n (truth) | n (classified) | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|---|---|
| **1** | 311 | 301 | 98.74% | 0.98 | 0.95 | 0.96 |
| **2** | 399 | 402 | 98.37% | 0.96 | 0.96 | 0.96 |
| **3** | 643 | 638 | 98.16% | 0.98 | 0.97 | 0.97 |
| **4** | 264 | 275 | 98.26% | 0.92 | 0.96 | 0.94 |
| **5** | 283 | 284 | 98.47% | 0.95 | 0.95 | 0.95 |

Comparison of traditional and proposed accuracy, precision, recall and F1 Score in case of graphical twitter sentiment analysis

TABLE VII. COMPARISON OF ACCURACY

| Accuracy for conventional model | Accuracy for proposed model |
|---|---|
| 97.84% | 98.74% |
| 97.53% | 98.37% |
| 96.84% | 98.16% |
| 97.32% | 98.26% |
| 97.63% | 98.47% |

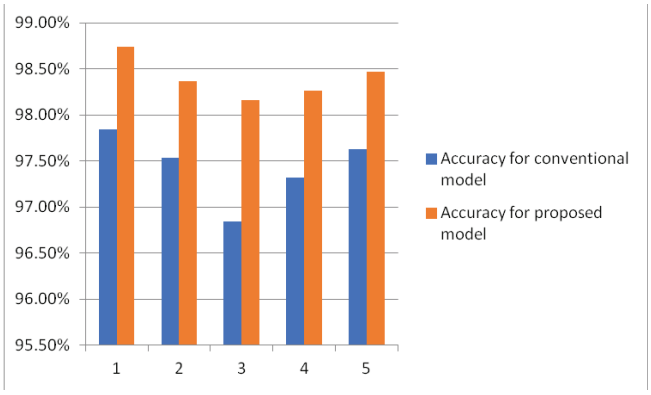


Fig. 5. Comparison of accuracy in case of graphical tweets

TABLE VIII. COMPARISON OF PRECISION

| Precision for conventional model | Precision for proposed model |
|---|---|
| 0.91 | 0.98 |
| 0.94 | 0.96 |
| 0.95 | 0.98 |
| 0.91 | 0.92 |
| 0.93 | 0.95 |

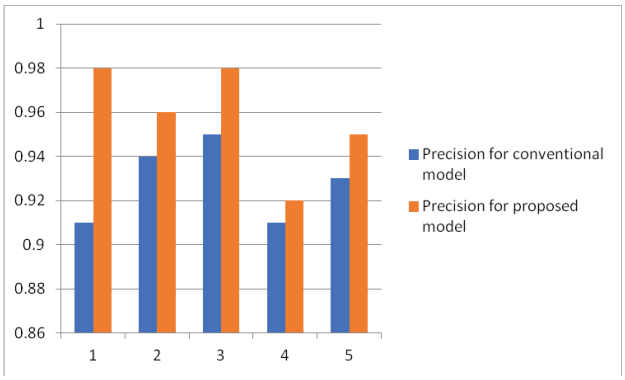


Fig. 6. Comparison of precision in case of graphical tweets

TABLE IX. COMPARISON OF RECALL

| Recall for conventional model | Recall for proposed model |
|---|---|
| 0.95 | 0.95 |
| 0.94 | 0.96 |
| 0.95 | 0.97 |
| 0.9 | 0.96 |
| 0.91 | 0.95 |

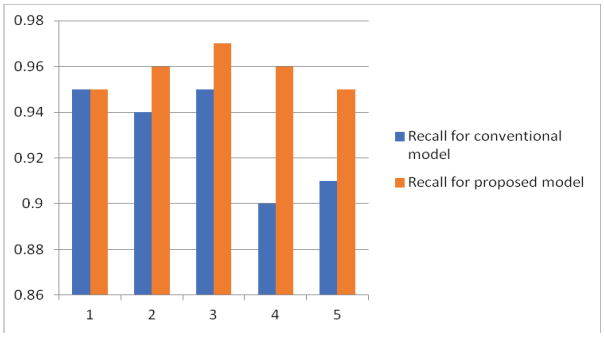


Fig. 7. Comparison of Recall in case of graphical tweets

TABLE X. COMPARISON OF F-SCORE

| F-Score for conventional model | F-Score for proposed model |
|---|---|
| 0.93 | 0.96 |
| 0.94 | 0.96 |
| 0.95 | 0.97 |
| 0.91 | 0.94 |
| 0.92 | 0.95 |

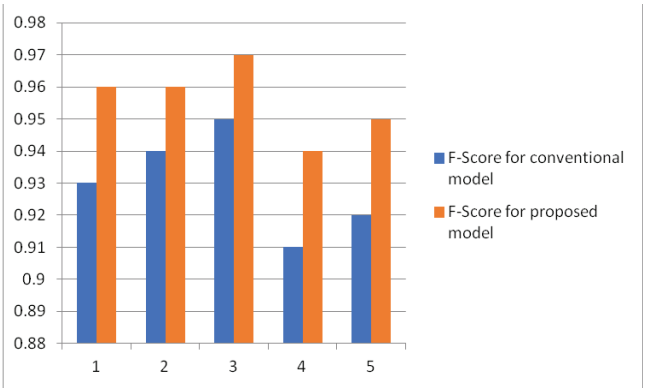


Fig. 8. Comparison of F1 Score in case of graphical tweets

## VII. CONCLUSION

The findings demonstrate that the proposed work provides a flexible strategy for predicting sentiment from a Twitter handle, by taking into consideration both visual and linguistic information. The proposed research has a number of benefits over the status quo, including a higher fscore, increased accuracy, and memory. Preprocessing has also resulted in a reduction in training time. For graphical simulation, the traditional and recommended total accuracy is 93.58% and 96%.

## VIII. FUTURE SCOPE

The research employed sentiment analysis, ML , CNN, and ANN as a summation. Research is meant to produce a more flexible and accurate answer. The categorization problem was solved by analyzing the sentiment of the data. Because of machine learning, automated systems may learn and grow on their own. The system then learns from its own mistakes and improves its own performance without the need for any human input. Data-driven judgments are made possible by this. Images are categorized using CNNs, a deep learning approach that assigns each picture a class and a label, which gives each image its own unique identity. Image classification using the CNN is a common part of machine learning research.

## ACKNOWLEDGMENT

In American English, the term "acknowledgment" is often spelled without the final e. The awkward "one of us (R. B. G.) thanks..." should be avoided at all costs. Just say "R. B. G. thanks..." instead. Acknowledgements of funding should be included in an unnumbered footnote on page 1.

## REFERENCES

[1] R. Collobert, J. Weston, L. Bottou, M. Karlen, K. Kavukcuoglu, and P. Kuksa. Natural language processing (almost) from scratch. Journal of Machine Learning Research, 12(Aug):2493–2537, 2011.

[2] K. Dave, S. Lawrence, and D. M. Pennock. Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In Proceedings of the 12th international conference on World Wide Web, pages 519–528. ACM, 2003.

[3] M. S. Elli and Y.-F. Wang. Amazon reviews, business analytics with sentiment analysis.

[4] S. Hota and S. Pathak. Knn classifier based approach for multi-class sentiment analysis of twitter data. In International Journal of Engineering Technology, pages 1372–1375. SPC, 2018.

[5] B. Liu and L. Zhang. A Survey of Opinion Mining and Sentiment Analysis, pages 415–463. Springer US, Boston, MA, 2012.

[6] C. Rain. Sentiment analysis in amazon reviews using probabilistic machine learning. Swarthmore College, 2013.

[7] R. Socher, A. Perelygin, J. Wu, J. Chuang, C. D. Manning, A. Ng, and C. Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In Proceedings of the 2013 conference on empirical methods in natural language processing, pages 1631–1642, 2013.

[8] Y. Xu, X. Wu, and Q. Wang. Sentiment analysis of yelps ratings based on text reviews, 2015.

[9] KumarRaviab, VadlamaniRavia , "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications", Knowledge-Based Systems, Volume 89, November 2015, Pages 14-46

[10] N. Zainuddin, A. Selamat, and R. Ibrahim, "Hybrid sentiment classification on twitter aspect-based sentiment analysis," Applied Intelligence, pp. 1-15, 2017.

[11] M. Z. Asghar, F. M. Kundi, S. Ahmad, A. Khan, and F. Khan, "T-SAF: Twitter sentiment analysis framework using a hybrid classification scheme," Expert Systems, vol. 35, no. 1, 2018.

[12] Alsaeedi, Abdullah & Khan, Mohammad. (2019). A Study on Sentiment Analysis Techniques of Twitter Data. International Journal of Advanced Computer Science and Applications. 10. 361-374. 10.14569/IJACSA.2019.0100248.

[13] Shathik, Anvar & Karani, Krishna Prasad. (2020). A Literature Review on Application of Sentiment Analysis Using Machine Learning Techniques. 2581-7000. 10.5281/zenodo.3977576.

[14] Liu, H., & Cocea, M. (2017). Fuzzy rule based systems for interpretable sentiment analysis. International Conference on Advanced Computational Intelligence (ICACI),1(1), 129–136. DOI: https://doi.org/10.1109/ICACI.2017.7974497

[15] Abo, M., Shah, N., Balakrishnan, V., & Abdelaziz, A. (2018). Sentiment analysis algorithms: Evaluation performance of the Arabic and English language. IEEE Expert,1(1), 1-5. DOI: https://doi.org/10.1109/ICCCEEE.2018.8515844

[16] Bansal, A., Gupta, C. L., & Muralidhar, A. (2019). A Sentimental Analysis for YouTube Data using Supervised Learning Approach. International Journal of Engineering and Advanced Technology (IJEAT), 8 (5).1-12

[17] Alsaeedi, A., & Khan, M. (2019). A Study on Sentiment Analysis Techniques of Twitter Data. International Journal of Advanced Computer Science and Applications, 10(1), 361–374. DOI: https://doi.org/10.14569/IJACSA.2019.0100248

[18] Sadhasivam, J., & Babu, R. (2019). Sentiment Analysis of Amazon Products Using Ensemble Machine Learning Algorithm. International Journal of Mathematical, Engineering and Management Sciences, 4(1), 508–520. DOI: https://doi.org/10.33889/IJMEMS.2019.4.2-041

[19] Hasan, A., Moin, S., Karim, A., & Shamshirband, D. (2018). Machine Learning-Based Sentimental Analysis for Twitter Accounts. Mathematical and Computational Applications, 23(1), 11-32. DOI: https://doi.org/10.3390/mca23010011

[20] Sultana, N., Kumar, P., Patra, M., Chandra, S., & Alam, S. (2019). Sentiment Analysis for Product Review. International Journal of Soft Computing, 09(1), 7-28. DOI: https://doi.org/10.21917/ijsc.2019.0266

[21] Raza, H., Faizan, M., Hamza, A., Mushtaq, A., & Akhtar, N. (2019). Scientific Text Sentiment Analysis using Machine Learning Techniques. International Journal of Advanced Computer Science and Applications,10(12), 157-165. DOI: https://doi.org/10.14569/IJACSA.2019.0101222

[22] Valencia, F., Gómez-Espinosa, A., & Valdés-Aguirre, B. (2019). Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning. International and interdisciplinary Journal Entropy, 21(6), 589. DOI: https://doi.org/10.3390/e21060589

[23] Daeli, N. O. F., & Adiwijaya, A. (2020). Sentiment Analysis on Movie Reviews using Information Gain and K-Nearest Neighbor. Journal of Data Science and Its Applications, 3(1), 1–7.DOI: https://doi.org/10.34818/jdsa.2020.3.2

[24] Kumar, S., Gahalawat, M., Roy, P. P., Dogra, D. P., & Kim, B.-G. (2020). Exploring Impact of Age and Gender on Sentiment Analysis Using Machine Learning. International Journal of Electronics, 9(2), 374. DOI: https://doi.org/10.3390/electronics9020374

[25] Shuhidan, S. M., Hamidi, S. R., Kazemian, S., Shuhidan, S. M., & Ismail, M. A. (2018). Sentiment Analysis for Financial News Headlines using Machine Learning Algorithm. International Conference on Kansei Engineering and Emotion Research,739(1), (64–72). DOI: https://doi.org/10.1007/978-981-10-8612-0_8

[26] Yogi, T. N., & Paudel, N. (2020). Comparative Analysis of Machine Learning Based Classification Algorithms for Sentiment Analysis. International Journal of Innovative Science, Engineering & Technology, 7(6),1-9.

[27] Suryawanshi, R., Rajput, A., Kokale, P., & Karve, S. S. (2020). Sentiment Analyzer using Machine Learning. International Research Journal of Modernization in Engineering Technology and Science, 02(06),1-12

[28] K. Sentamilselvan, D. Aneri, A. C. Athithiya, P. Kani Kumar. (2020). Twitter Sentiment Analysis using Machine Learning Techniques. International Journal of Engineering and Advanced Technology (IJEAT), 9(3), 1-9. DOI: 0.35940/ijeat.C6281.029320

[29] K. Sentamilselvan, D. Aneri, A. C. Athithiya, P. Kani Kumar. (2020). Twitter Sentiment Analysis using Machine Learning Techniques. International Journal of Engineering and Advanced Technology (IJEAT), 9(3), 1-9. DOI: 0.35940/ijeat.C6281.029320

[30] https://mk0ecommercefas531pc.kinstacdn.com/wp-content/uploads/2019/12/sentiment-analysis.png

[31] https://miro.medium.com/max/361/0*ga5rNPmVYBsCm-lz.

[32] https://i.ytimg.com/vi/VXt9SQx5eM0/maxresdefault.jpg