iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** VI **Month of publication:** June 2022

DOI: https://doi.org/10.22214/ijraset.2022.44772

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VI June 2022- Available at www.ijraset.com

Fake News Detection Using Feature Selection and Deep Learning

K. Sangeeta[1], Thota Gowri Priya[2], Susmitha Patro[3], Allu Goutham[4], Kinjarapu Jeevana Jyothi[5], Muvvala Anil Kumar[6]
[1]Sr. Asst. Professor, Department of CSE, AITAM, Tekkali, Andhra Pradesh
[2, 3, 4, 5, 6]B.Tech. Students, Department of CSE, AITAM, Tekkali, Andhra Pradesh

Abstract: The days have come when people are increasingly using apps on their smart devices. Every day everyone generates millions of data per second. As for usage increases, so soon negative actions such as rumors and false stories on social media also increase. To resolve this issue, we have proposed a "Fake News Detection using Feature Selection and Deep Learning" feature. To develop an automated rumor detection model, this study prefers a hybrid model to separate rumors using an Deep Learning (Convolution Neural Network) and a filter-wrapper (Artificial Bee Colony) classified by the Naïve Bayes classifier as a test algorithm. The feature set uses a mixed model with CNN as an Deep learning model and ABC as a training data filter model and the results are applied to the Naïve Bayes classifier to calculate accuracy.
Index Terms: Convolution Neural Network, Artificial Bee Colony, Naive Bayes Classifier

I. INTRODUCTION

False stories or misleading information presented as stories. False stories often have the effect of damaging the reputation of an individual or an organization or of making money through advertising campaigns.

Finding and stopping rumors is important as social media is a fertile ground for spreading and the source of rumors. Rumors are not any information that is disseminated to the public without adequate awareness or confirmation that could support their legitimacy.

A. Rumor Discovery

Rumors may be a current story or a report of uncertain or uncertain truth. In addition, it may be described as a related degree in a test statement that starts with one or more sources and opens up over time. Rumor detection is the process of determining the authenticity of any event.

Research into the emergence of rumors and verification tools has become increasingly popular as communication penetration has increased. This allows both users and professionals to collect news and facts in real-time, but with the problematic side effect of unconfirmed natural information.

The rumor segregation system consists of four parts: rumor detection, rumored tracking, rumor segregation, and factual rumor classification. When it comes to designing a rumor-sharing system, the main thing that determines the methods to be used is the temporary features i.e., new rumors that emerge during the news. Rumors from the news media are often unprecedented in history. Therefore, rumors need to be detected automatically and the rumor segregation system needs to be able to deal with new, anonymous rumors, considering that the training data available in the system may be different from what it will see later. In these cases, when early detection and rumor correction are essential, the distribution of the post requires real-time processing. Long-term rumors are being discussed at length. Some rumors can spread for a long time unless their authenticity is established with certainty. These rumors sparked intense interest despite the difficulty of finding the real truth. In addition, the system can use historical conversations about rumors to separate ongoing conversations, where words are less likely to be different, so a separator built into old data can still be used for new data. Contrary to recent rumors, in long-term rumors, the processing is often backward, so the post does not have to be processed in real-time.

II. LITERATURE SURVEY

Getting gossip is important, remembering the volume and speed of user-generated information on social media. The social media platform allows for the distribution of information regardless of source status and true value. Transferring and sharing content combined with a lack of verification fuels rumors as it allows for exchange and broadcast at an unparalleled level. However, this can be dangerous if users are exposed to harmful or unwanted content.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VI June 2022- Available at www.ijraset.com

Yang, Fan, Yang Liu, Xiaohui Yu, and Min Yang have proposed that how to get rumors automatically. In this paper they have compiled a comprehensive set of microblogs that are confirmed as false rumors based on information from official rumors. service provided by Sina Weibo. Then they explore a vast set of features that can be pulled out of microblogs, and train a class divider to automatically detect rumors of a mixed set of true information and false information.

Kwon and Sejeong et al have proposed their strategy for the detection of rumors on social media. This paper focuses on a detailed discussion of data sets and advanced methods of acquisition of rumors. In addition, this paper sheds light on the supervised and unsupervised methods as well as in-depth learning methods to detect rumors.

Yang, Zhifan et al ‘s paper proposed how to Identify Emerging Rumors of Social Media With Hot Topic Detection. Introducing the novel is a way to find a hot topic that involves identifying explosive words and modeling multi-dimensional sentences to automatically detect hot topics that emerge to identify rumors. We do a complete set of tests on two sets of data from a real-world social media platform. Experimental results show that our emerging hot-field media identification with hot topic discovery works well in both the news set and the twitter data set, and combining hot topic discovery with rumors is possible to complete real-time gossip detection.

Granik, Mykhailo, and VolodymyrMesyura have shown an easy way to get false news through the inexperienced Bayes section. This method was used as a software program and tested against a set of Facebook news post data. We found approximately 74% segment accuracy in the test set which is a good result considering the relative simplicity of the model.

Chen, Weiling, Chai Kiat Yeo, Chiew Tong Lau, and Bu Sung Lee have proposed that exhibitions to provide a comprehensive and complete overview of confusing discovery research. We have compiled the existing strategies into different categories based on the basic approach adopted for each process. In each section we have identified important assumptions, using techniques to distinguish between normal and bizarre behaviors. When applying a given process to a particular domain, these ideas can be used as guidelines for evaluating the effectiveness of a strategy in this domain.

Wang, Shihan, and Takao Terano have shown the patterns that cover both the structural and behavioral aspects of the rumors first proposed to distinguish false rumors in legitimate matters. The pattern corresponding to the graph based on the novel is also explained in order to detect rumors patterns in the distribution of social media data. Compared to the rumored and non-rumored Twitter data, our selected rumored patterns contain distinctive rumored features in the interim series.Most social media platforms allow users to create groups based on their interests; however, these groups may be echo chambers where participants ’views are amplified and reinforced.

S. No.	Dataset	Techniques	Evaluation Parameters	Reference
1.	Sina Weibo	SVM	Precision, Recall, F-score	Yang, Fan, Yang Liu, Xiaohui Yu, and Min Yang. (2012). "Automatic Discovery of Rumors in Sina Weibo." In discussions of the ACM SIGKDD Working Summit on Mining Data Statistics, 13.
2.	Twitter	Decision tree, SVM, Random Forest	Accuracy, Precision, Recall, F1	Kwon, Sejeong, et al. (2013). "Outstanding Features of Rumor Distribution on Online Social Media." 2013 IEEE 13th International Conference on Data Mining, 1103–8.
3.	News, Twitter	Logistic, Naïve Bayes, Random Forest	Precision, Recall, F-measure	Yang, Zhifan, et al. (2015). "Identifying the Emerging Rumors of Public Affairs on the Discovery of a Hot Topic." 2015 12th Web Information System and Application Conference (WISA), 53–58.

4.	Facebook	Naïve Bayes	True Positive, False Positive	Granik, Mykhailo, and Volodymyr Mesyura. (2017). "False News Detection using the Naive Bayes Classifier." 2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON), 900-903.
5.	Sina Weibo	Factor analysis of mixed data (FAMD)	Precision	Chen, Weiling, Chai Kiat Yeo, Chiew Tong Lau, and Bu Sung Lee. (2016). "Behavioral Deviation: The Perspective on Unusual Discovery of Rumors. ' 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (ICON), 1–7.
6.	Twitter	Graph-based pattern matching algorithm	Tf-idf	Wang, Shihan, and Takao Terano. (2015). "Discovering Patterns of Rumors in the Spreading of Social Media." 2015 IEEE International Conference on Big Data (Big Data), 2709–15.
7.	PHEME Rumor	Naïve Bayes, Filter-Wrapper Optimization	Precision, Recall, F-score	Kumar, A., Bhatia, M.P.S. & Sangwan, "S. R. The discovery of the rumor is based on in-depth reading and selection of the filter feature of the twitter data set ". Multimed Tools Appl (2021).

III. PROPOSED PROCEDURE

To achieve our goal of developing a deep learning model to classify stories as fiction or reality, we need to perform the following tasks in the same sequence as stated.

1) Data Collection and Analysis
2) Pre-processing data
3) Release of the text element
4) Using a classification algorithm
5) Classifying stories as fiction.
6) Modeling.

Text features are studied using the CNN model combined with the advanced vector-generated feature using the filter wrap method, ABC. The improved vector was then used to train the Naïve Bayes stage of editing in the CNN exit layer. Based on the required model parameters, we classify test data as fake or factual data with the best accuracy results.

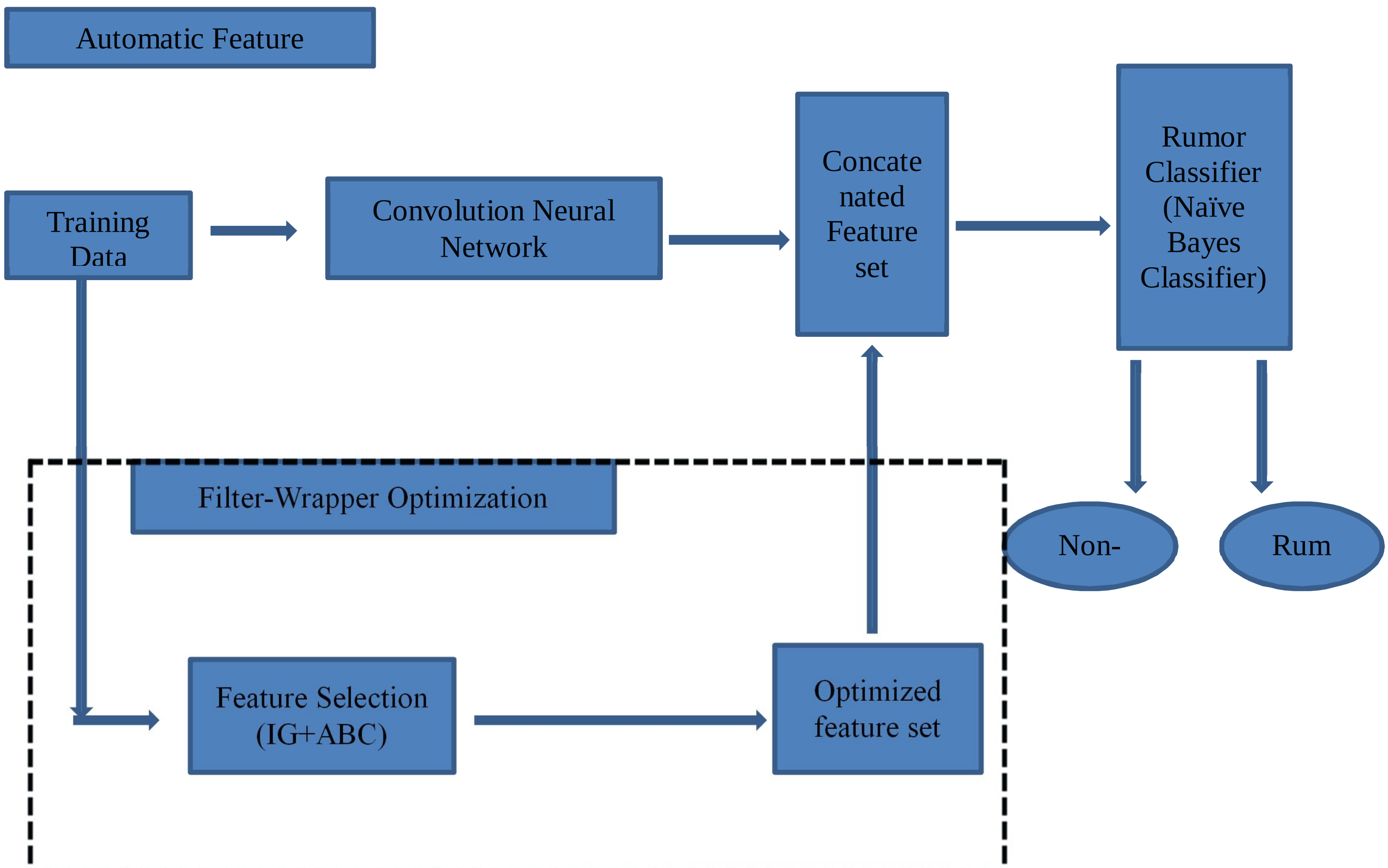
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VI June 2022- Available at www.ijraset.com

Integrated neural network integration with filtering selection options includes the following components:

a) CNN automatic reading feature
b) ABC selection feature enhanced
c) NB for rumor classification

The first thing to start and train is the Convolutional Neural Network (CNN) seeded using GloVe Embeddings. Glove embedding creates word vectors based on context. The model uses a four-layer architecture known as convolution, pooling, dense, and flatten layer. In the dense layer, we used the Relu activation function and in the density, we used SoftMax. The layer that comes out of our model has a Naïve Bayes section. This section takes a set of integrated features obtained by combining readable vector presentations from CNN (high cover layer output) and a set of appropriate features generated using ABC (Artificial Bee Colony) in a training data set. Finally, the NB category classifies posts as rumors or non-rumors.

A. Architecture



1) Data Set

Content and metadata are posted on Twitter that you think are associated with false news and factual data. First, we load the database, once the database has been uploaded and process the data.

2) Data Processing

Social media data is not very streamlined - most of it is informal communication with typos, slang, incorrect grammar, etc. The desire to increase efficiency and reliability has made it mandatory to develop resource use strategies to make informed decisions. For better details, it is necessary to clean up the data before it can be used to predict the model. To this end, a basic preliminary analysis was performed on News training data. This step is built of:

Data Cleaning

While reading data, we receive data in a formal or informal format. The formal format has a well-defined pattern while unstructured data does not have the correct format. Between the two structures, we have a semi-structured format that is relatively better built than the informal format. Clearing text data is needed to highlight the features that we will need for our deep learning plan to be considered. Cleaning (or pre-processing) data usually consists of a few steps:

a) *Remove Punctuation Marks:* Punctuation can give systemic context to a sentence that supports our understanding. But in our vector that counts the number of words and not the context, it does not include the value, so we delete all special characters. Ex .: How are you? -> Howareyou
b) *Tokenization:* Token making divides the text into units such as sentences or words. Provides structure for pre-built text. e.g. Platao Plomo -> 'Plata', 'o', 'Plomo'.
c) *Delete Expressions:* Stop words are common words that may appear in any text. They do n't tell us much about our data so we delete them. Eg: silver or lead is good for me-> silver, lead, good.
d) *Stemming:* The stemming helps to reduce the word to its stem. It usually makes sense to handle related words in the same way. It removes enough, such as "ing", "ly", "s", etc. in a simple legal way. Reduce the total number of words but often real words are ignored. Eg .: Granting, Authority -> Right.Note: Some search engines handle words with the same stems.
e) *Lemmatization:* It is the process of putting together different types of the translated word. Therefore, they can be analyzed as a single entity. It's the same with constipation but it brings context to the words. Thus, it associates words that have the same meaning in one word.

3) Feature Extraction

GloVe Embeddings: GloVe is an unregulated learning algorithm for receiving vector presentation presentations. Training is done on integrated global word counts that take place together in the chorus, and the resulting presentations show interesting sub-structures of the vector space name.

B. Convolutional Neural Network

The Convolutional Neural Network, also known as CNN or ConvNet, is a segment of neural networks focused on data processing.
The convolution layer is the building block of CNN. Contains a large part of the network accounting burden. This layer generates dot production between two matriculants, where one matrix is a set of readable parameters also known as a kernel, and the other matrix is a limited part of the reception field. The kernel is smaller in size than the image but much deeper.
The integration layer replaces the network output in certain areas by obtaining a summary of the nearest output statistics. This helps to reduce the size of the representation area, which reduces the required number of calculations and weights. The merging function is processed throughout each piece of representation.

C. Artificial Bee Colony

Artificial Bee Colony (ABC) is one of the algorithms recently described by Dervis Karaboga in 2005, inspired by the brilliant behavior of honey bees. ABC as a development tool provides a population-based search process in which so-called restaurants are replaced by artificial bees over time and the bee aims to find food sources with high amounts of nectar and ultimately those with high nectar. In the ABC system, artificial bees roam the multi-dimensional search area while others (hired and observant bees) select food sources based on their experience with their hive comrades and repair their hives. Others (scouts) fly and choose food sources without the use of knowledge. If the nectar value of a new source is higher than the previous one in their memory, they memorize a new position and forget the past. Thus, the ABC program incorporates local search methods, performed by hired bees and observers, and international search methods, controlled by spectators and scouts, which attempt to balance the testing process with exploitation.

D. Naïve Bayes Classifier

The Naïve Bayes algorithm is a supervised learning algorithm, based on the Bayes theorem and used to solve classification problems.
It is widely used to classify text that includes high-quality training databases. It is a system of possible classification, which means that it predicts based on the possibilities of an object.

The Naïve Bayes algorithm is made up of two names Naïve and Bayes, which can be defined as:

- *Naïve:* It is called Naïve because it assumes that the occurrence of a certain phenomenon independent on the occurrence of other factors. As if the fruit were characterized by color, shape, and taste, then the red, round, and sugary fruit is considered an apple. So each factor contributes to the identification of the apple without the dependence on the other.
- *Bayes:* It is called Bayes because it is based on the principle of the Bayes 'Theorem.

Bayes Theorem

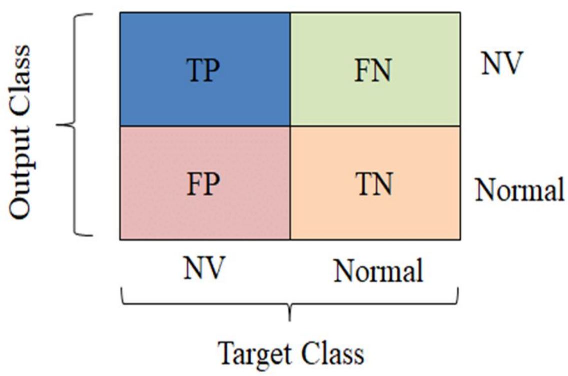
- Bayes theory is also known as the Bayes' Rule or the Bayes law, which is used to determine the probability of a hypothesis by prior knowledge. Subject to conditional opportunities.
- The theory formula for Bayes is given as:

$$P(A|B)=\frac{P(B|A)P(A)}{P(B)}$$

Where,
P (A | B) Subsequent Probability: Probability hypothesis A is targeted B event.
P (B | A) Likelihood Probability: Probability for the evidence provided that the hypothesis probability is real.t
P (A) Previous Probability: Probability for hypothesis before looking at the evidence.
P (B) Marginal Probability: Probability for Evidence.

E. Confusion Matrix

It is a common way to present positive predictions (TP), true negative (TN), false (FP), and negative predictions (FN). Those numbers are presented in the form of a matrix where the Y-axis shows the true classes while the X-axis indicates the predicted classes.



• True Positive (TP) - the number of rumors identified correctly
• False Positives (FP) —several rumors that can be misdiagnosed as rumors
• False Negatives (FN) —several rumors that have been mislabeled
• True Negatives (TN) —several well-defined rumors.

F. Classification Report

Accurate metrics are often used to describe how much is considered right, or false. A high degree of accuracy indicates a good model, but as we train the differentiating model here, false positives can have negative consequences. Accuracy = (TP + TN) / (TP + TN + FP + FN). Similarly, if an article is predicted to be false while containing factual data, this could create trust issues. Therefore, we used three other metrics that considered incorrectly classified observations, namely, accuracy, recall, and F1-score.
A recall is the total number of good categories made out of class. The ratio between the number of articles predicted to be true and the total number of true articles.
Recall = TP / (TP + FN).
An accurate score is a measure of true points in all actual events predicted. Specifically, we define accuracy as a percentage of positive (true) predictions marked as true:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VI June 2022- Available at www.ijraset.com

Precision = TP / (TP + FP)

F1-score is a measure of accuracy compared to memory. It takes a harmonic measure of both. Therefore, both positive and negative perceptions are considered. F1-score can be calculated using the following formula:

F1 - score = 2 (Precision × Recall) / (Precision + Recall)

IV. RESULT

The performance of the proposed model has been evaluated for each event within the dataset.

A. *Output of CNN Model*

1) *CNN model for Dataset*

```
=========================
Fitting the simple convolutional neural network model
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 1000)]            0

 embedding (Embedding)       (None, 1000, 100)         4700

 conv1d (Conv1D)             (None, 996, 32)           16032

 max_pooling1d (MaxPooling1D  (None, 199, 32)          0
 )

 conv1d_1 (Conv1D)           (None, 195, 32)           5152

 max_pooling1d_1 (MaxPooling  (None, 39, 32)           0
 1D)

 conv1d_2 (Conv1D)           (None, 35, 32)            5152

 max_pooling1d_2 (MaxPooling  (None, 1, 32)            0
 1D)

 flatten (Flatten)           (None, 32)                0

 dense (Dense)               (None, 32)                1056

 dense_1 (Dense)             (None, 2)                 66

=================================================================
Total params: 32,158
Trainable params: 32,158
Non-trainable params: 0
_________________________________________________________________
Epoch 1/30
1122/1122 [==============================] - 208s 185ms/step - loss: 0.7476 - acc: 0.4841 - val_loss: 0.6929 - val_acc: 0
.5221
Epoch 2/30
```

1122/1122 [==============================] - 192s 171ms/step - loss: 0.6907 - acc: 0.5387 - val_loss: 0.6887 - val_acc: 0
.5434
Epoch 3/30
1122/1122 [==============================] - 193s 172ms/step - loss: 0.6876 - acc: 0.5550 - val_loss: 0.6859 - val_acc: 0
.5594
Epoch 4/30
1122/1122 [==============================] - 190s 169ms/step - loss: 0.6849 - acc: 0.5726 - val_loss: 0.6832 - val_acc: 0
.5733
.
.
.
.
.
.
Epoch 29/30
1122/1122 [==============================] - 191s 170ms/step - loss: 0.5347 - acc: 0.7673 - val_loss: 0.5283 - val_acc: 0
.7694
Epoch 30/30
1122/1122 [==============================] - 196s 174ms/step - loss: 0.5234 - acc: 0.7727 - val_loss: 0.5168 - val_acc: 0
.7770

2) Model Training Completed

-> Correct predictions: 27933.0

-> Total number of test examples: 35904

-> Accuracy of model: 0.7779913101604278

Confusion Matrix for CNN MODEL:
[[14789 3934]]
[[5417   11764]]

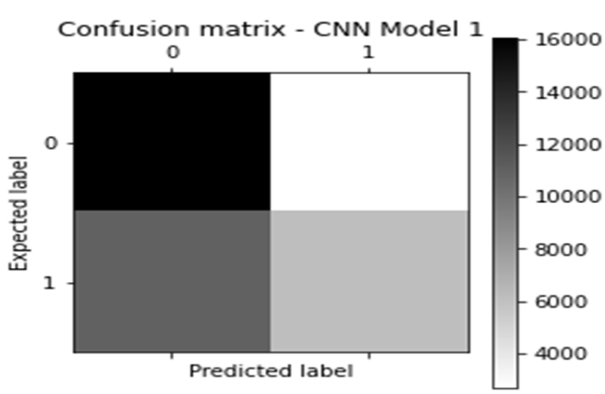


Fig. Confusion matrix for CNN MODEL.

3) Features Extracted From ABC:

New.csv
Epoch 1
forward pass
evaluating

Best distance so far 0.0
Best route so far ['30,"', '96,U.S.', '104,Failed']
Bees are making decision to be recruiter or follower
number of recruiter 500
Bees are choosing their recruiter

Epoch 2
forward pass
evaluating
Best distance so far 0.0
Best route so far ['30,"', '96,U.S.', '104,Failed', '38,', '89,Alabama', '126,Senators']
Bees are making decision to be recruiter or follower
number of recruiter 0
Bees are choosing their recruiter
.
.
.
.
.
Epoch 49
forward pass
evaluating
Best distance so far 0.0
Best route so far ['38,', '71,"', '113,Callista', '24,', '44,', '86,"Trump', '60,"', '55,', 'index,title,text,subject,date,label', '21,"', '97,"Trump', '112,House', '78,', '123,U.S.', '16,', '117,Factbox:', '37,', '59,', '76,', '50,', '61,', '54,"', '81,U.S.', '85,"White', '99,Treasury', '119,Senate', '82,Senior', '70,', '73,"', '92,"Factbox:', '39,"', '106,Companies', '67,', '107,"Trump', '36,"', '98,U.S.', '111,McConnell', '104,Failed', '125,Second', '105,"Trump', '42,', '17,', '58,', '96,U.S.', '35,', '103,Second', '52,', '110,Alabama', '1,', '22,', '40,', '124,House', '95,Virginia', '10,', '49,', '11,"', '108,Mexico', '84,Trump', '126,Senators', '66,', '3,', '27,', '13,', '56,', '32,', '46,', '75,', '109,Senate', '20,', '121,House', '48,', '41,', '6,', '65,"', '53,', '118,"In', '116,"Congress', '8,"', '29,', '5,', '31,"', '90,Jones', '47,', '14,"', '87,"Factbox:', '28,"', '127,U.S.', '63,', '102,Trump', '26,', '69,', '2,', '57,', '72,', '12,', '91,New', '77,', '93,"Trump', '83,FBI', '34,', '25,', '89,Alabama', '101,Exclusive:', '15,', '51,', '30,"', '19,', '4,', '9,"', '33,"', '64,"', '45,', '80,"As', '43,', '100,Federal', '23,', '7,"', '62,', '18,', '68,', '94,Man', '122,U.S.', '115,Exclusive:', '79,', '88,Trump', '114,"As', '74,', '128,"Short-term', '120,"Trump']
Bees are making decision to be recruiter or follower
number of recruiter 425
Bees are choosing their recruiter

4) Classification Report

	Precision	recall	f1-score	support
-1	1.00	1.00	1.00	1
0	1.00	1.00	1.00	5
1	1.00	1.00	1.00	1
Accuracy			1.00	7
Macro avg	1.00	1.00	1.00	7
Weighted avg	1.00	1.00	1.00	7

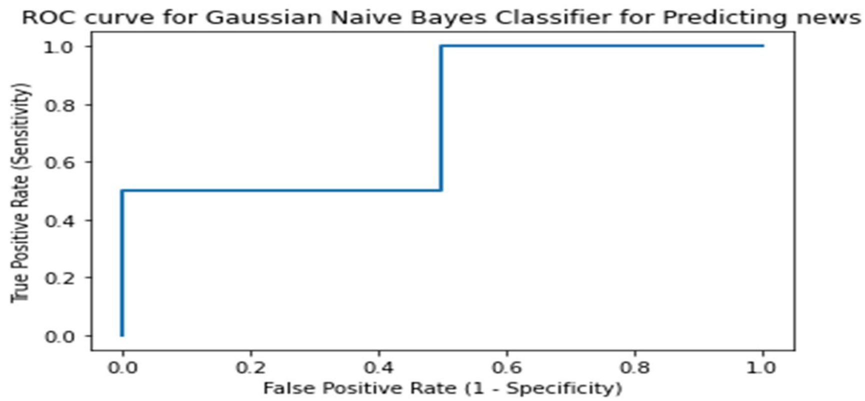


Fig:4. Naïve Bayes Classifier

V. CONCLUSION AND FUTURE PLAN

When times are hard, rumors spread. Rumors abound in the social world that are visible because of the uncertainty and significance of the situation. Information retention is very important. As a solution to dispel online rumors, this study provided a novel model of real-time rumor segregation that reads integrated features in high-quality features from CNN and advanced features obtained using mixed filter-meta-heuristic Artificial bee colony. The process of selecting the threat factor to improve.

Our method only uses text-based features while meta-features such as tweet rewriting and user-based features can be read separately to create a robust model to reveal rumors. In addition, the use of country-specific content written in the vernacular also includes language issues in obtaining rumors. As a future approach, the following stages of the rumor mill can be processed using a mixed model. Also, as this work introduces text-based discovery, contextual modeling can be done to improve the detection and dismissal of rumors. In addition, it is also important to use information from different social media platforms and languages to verify rumors automatically.

REFERENCES

[1] Kumar A, Shrivastava A (2020) The discovery of rumors on a benchmark database using residual networks based on attention. Int J Adv Sci Technol 29 (3): 14682.
[2] Ma J, Gao W, Mitra P, Kwon S, Jansen BJ, Wong KF, Cha M (2016) Receives rumors from microblogs with common emotional networks.
[3] Fazil, Mohd, and Muhammad Abulaish. (2018). "A Hybrid Way to Get Automatic Spammers on Twitter." IEEE Transactions on Information Forensics and Security 13 (11): 2707–19.
[4] Granik, Mykhailo, and Volodymyr Mesyura. (2017). "False News Detection using the Naive Bayes Classifier." 2017 IEEE First Ukraine Conference on Electrical and Computer Engineering (UKRCON), 900-903
[5] Chen, Weiling, et al. (2018). "Unchecked Retrieved Retrieval Detection of Users Using Neural Networks." Recognition Letters Pattern 105: 226–33.
[6] Pathak, Ajeet Ram, Manjusha Pandey, and Siddharth Rautaray. (2018). "Use of Deep Acquisition Learning." Procedia Comput. Sci 132: 1706-17.
[7] Ajao, Oluwaseun, Deepayan Bhowmik, and Shahrzad Zargari. (2018). "False News Identification on Twitter by Hybrid models CNN and RNN." Proceedings of the 9th International Conference on social media and Society, 226–30.
[8] Li G, Dong M, Yang F, Zeng J, Yuan J, Jin C, and Zheng B (2020 Misinformation-oriented expert finding in social networks. World Wide Web 23 (2): 693–714.
[9] Kumar A, Sangwan SR, Nayyar A (2019) The discovery of rumors on Twitter using advanced particle filters. Multimed Tools Appl 78 (17): 24083–24101.
[10] Jianqiang Z, Xiaolin G, Xuejun Z (2018) Deep convolution neural networks for emotional analysis Twitter. Access to IEEE 6: 23253–23260.
[11] Cao J, Guo J, Li X, Jin Z, Guo H, Li J (2018) Automatic rumor detection on microblogs: a survey. ArXiv preprint arXiv: 1807.03505
[12] Alkhodair SA, Ding SH, Fung BC, Liu J (2020) Finds rumors of emerging news topics appearing on social media. Inf Processes Manag 57 (2): 102018
[13] Liu Y, Xu S (2016) Discovering rumors by modeling information networks. IEEE Trans Comput Soc Syst 3 (2): 46–62.
[14] Jianqiang Z, Xiaolin G, Xuejun Z (2018) Deep convolution neural networks for Twitter motion analysis. Access to IEEE 6: 23253–23260
[15] Chang, Cheng, Yihong Zhang, Claudia Szabo, and Quan Z Sheng. (2016). "Receiving Extra User and Political User Rumors on Twitter." At the International Conference on Advanced Data Mining and Requests, 751–63.