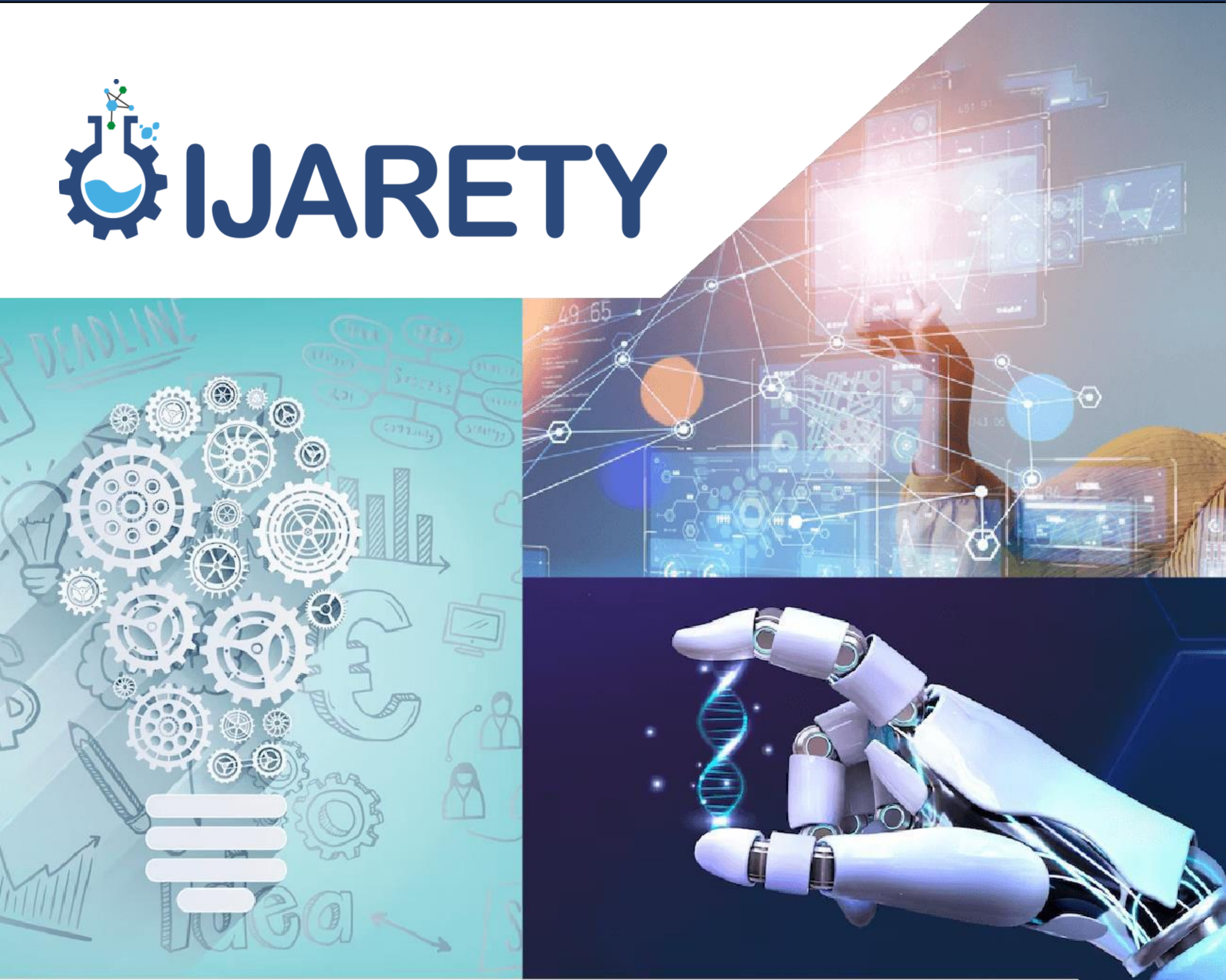
IJARETY



International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 2, March-April 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

Classifying Fake Statements Using Natural Language Processing

Kunaparaju Venkata Jhansi Rani[1], Kota Bhavani[2], Manne Krupa Mani[3], Kallempudi Vagdevi[4]

Associate Professor, Department of CSE, Eluru College of Engineering & Technology, Eluru, India[1]

B. Tech Student, Department of CSE, Eluru College of Engineering & Technology, Eluru, India[2,3,4]

ABSTRACT: This paper presents an NLP-driven approach to identifying fake statements made by public figures. The system employs natural language processing (NLP) techniques to analyze textual data and classify statements as true or false. Given the rise of digital media, misinformation has become a global challenge, influencing public opinion and political discourse. Fake news spreads rapidly through social and mainstream media, making fact-checking increasingly difficult. The proposed system processes statements independently, without relying on metadata, using techniques such as tokenization, stemming, and stop-word removal. This method enhances the accuracy of classification by focusing on the linguistic features of statements. Future improvements may incorporate additional contextual data to refine detection accuracy further. Developed using Python and MySQL, this system provides a scalable and efficient solution to combat misinformation, contributing to more reliable information dissemination in the digital age.

KEYWORDS: Classification, Fake Image, Natural Language Processing and Detection.

I. INTRODUCTION

The progress in modern informational technologies brings us to the era where information is as accessible as ever. It is possible to find the answers to the questions we are interested in in a matter of seconds. Availability of mobile devices makes it even more convenient for the users. This factor changed the way of how people get the news information a lot. Every mainstream mass media has its own online portal, Facebook account, Twitter account etc., so people can access news information really quickly. Unfortunately, the news information that we get is not always true. Paradoxically, the Internet makes it harder to fact check the available information, because there are too many sources that often even contradict each other. All of this caused the emergence of fake news.

Mass media and social media have a great influence on a public. There are sides that are interested in using this to achieve their political goals with the help of fake news. They provide false information in form of news to manipulate people in different ways. There exist lots of websites with a single purpose of spreading of false information. They publish fake news, propaganda materials, hoaxes, conspiracy theories in disguise of a real news information. The main purpose of fake news websites is to affect the public opinion on certain matters (mostly political). Examples of this may be found in Ukraine, United States of America, Great Britain, Russia and many other countries. Thus, fake news is a global issue and an important challenge to tackle. There is a belief that fake news problem may be solved automatically, without human interference, by means of artificial intelligence. This cause by the rise of deep learning and other artificial intelligence techniques showed us that they can be very effective in solving complex, sometimes even non-formal classification tasks. This article describes a way for classification of short political statements by means of artificial intelligence. Several approaches were implemented and tested on a data set of a statement made by real-life politicians The data set that was used for training and testing was collected by a RAMP studio team. It contains of short statements made by famous public figures. Six possible labels were available for the statement. They are: Pants on Fire!' (completely false), 'False', 'Mostly False', 'Half-True', 'Mostly True' and 'True'.

Each entry in the data set, besides the statement itself, also contains a lot of metadata. It contains the date when the statement was made, the job of the public figure who made that statement, the source where the statement was taken from, some keywords that characterize the content of the statement and many more other features. The data set consists of 10460 entries in total (7569 of them were provided for training and 2891 for testing). There are more than 2000 different sources of the statements. The RAMP studio team collected the data set using PolitiFact website. The PolitiFact is a project operated by Tampa Bay Times in which reporters from the Times and affiliated media factcheck statements by members of the United States Congress, the White House, lobbyists and interests groups. They publish original statements and their evaluations on the PolitiFact.com website, and assign eacit h a "Truth-O-Meter" rating .

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

PolitiFact.com was awarded the Pulitzer Prize for National Reporting in 2009 for "its fact-checking initiative during the 2008 presidential campaign that used probing reporters and the power of the World Wide Web to examine more than 750 political claims, separating rhetoric from truth to enlighten voters". At some points PolitiFact was criticized by both liberal and conservative wings of American politics, but nevertheless it is a viable source of fact-checked information. This makes a data set useful for creating a system which will classify statements as true or false. Before actually applying the artificial intelligence algorithms to the data, it should be pre-processed. First of all it was decided to use only the statements themselves for classification purposes. This means that none of the metadata provided is used for classification. The classification algorithm might actually be improved in the future by taking into account this metadata. The steps that were used for the pre-processing are the following:

1. Splitting the statements into separate tokens (words).
2. Removing all numbers.
3. Removing all punctuation marks.
4. Remove all other non-alpha characters
5. Applying the stemming procedure to the rest of the tokens.

In linguistic morphology and information retrieval, stemming (or lemmatization) is the process of reducing inflected or derived words to their word stem, base or root form – generally a written word form. This helps to treat similar words (like “write” and “writing”) as the same words and might be extremely helpful for classification purposes. Removing stop words. Stop words are the words occur in basically all types of texts. These words are common and they do not really affect the meaning of the textual information, so it might be useful to get rid of them. Substitution of words with their tf-idf scores. In information retrieval, tf–idf, which is a short for term frequency–inverse document frequency”, is a numerical statistic measure reflects the importance of a certain word to a document in a collection or corpus. The tf-idf value increases proportionally to the number of times a word appears in the document and decreases proportionally to the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general. According to tf-idf, the weight of a term that occurs in a document is proportional to its frequency, and the specificity of a term can be calculated as an inverse function of the number of documents that contain the specified term. Several artificial intelligence algorithms were used for statement classification. All of them are implemented by scikit-learn (a library for Python programming language). For all of the algorithms two different metrics were measured:

- Classification accuracy based on six categories available
- Binary classification accuracy.

This metric counts the accuracy as if there were only 2 possible categories for the statement – true (based on the last three categories described above) and false (based on the first three categories described above) For all of the methods the provided data set with known labels was split into training and validation data sets. The training data set was used for the actual process of training of the machine learning models. The validation data set was used or some very basic model tuning. The idea is that having a validation data set we can iteratively tune the machine learning model by repeating the following process:

- Change a subset of machine learning model meta parameters.
- Train it on the training data set.
- Measure its performance on the validation data set.

In the end, usually the model, which performed the best on the validation data set, is chosen as a final model. Its performance on the testing data set is considered as an unbalanced estimate of how well the model performs on previously unseen data.

A. Classification with logistic regression Logistic regression is a statistical method for analyzing a data set in which there are one or more independent variables that determine an outcome [8]. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). For the cases when there are more than two labels, the strategy, which is called “One versus all”, is used. In this strategy every category is binary classified against its inverse a fictional category that states that the example does not belong to the current category). The category with the highest score is picked as a result of a classification. Logistic regression is one of the simplest machine learning techniques. It is easy to implement and easy to interpret. It is usually a good idea to implement logistic regression

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

classifier before proceeding with a more complex approach because it gives you an estimate of how well machine learning algorithms will perform on this specific task. It also helps to eliminate some basic implementation bugs regarding data set treatment. The results that were achieved for logistic regression classifier are the following:

- classification accuracy – 72%
- binary classification accuracy – 75%

B. Classification with naive Bayes classifier In artificial intelligence, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes theorem with strong (naive) independence assumptions between the features. Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. It is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. Naive Bayes were widely used for e-mail filtering problem. They were invented in the middle of the 90s and they were widely used for classification of e-mails as spam or not spam. Naive Bayes typically use bag of words features to classify texts. Naive Bayes classifiers usually correlate the use of tokens (typically words, or sometimes other constructions, syntactic or not), with the classes that are used for classification, and then apply Bayes theorem to calculate a probability that a text belonging to a certain class. Using naive Bayes classifier is easy to use for both binary and multi-label classification. For the task, described in the paper it is possible to calculate probabilities of the fact that each given statement belongs to the specific group.

1.1 MOTIVATION

The rapid spread of misinformation has severe consequences, including erosion of trust in institutions, manipulation of public opinion, and harm to individuals and communities. To mitigate these risks, it is essential to develop effective tools for identifying and flagging fake statements, and NLP offers a promising solution by enabling the automated analysis and classification of text-based information.

1.2 PROBLEM DEFINITION

Identifying fake statements amidst the vast amount of online information has become a daunting task. The challenge lies in developing an NLP-based system that can accurately classify statements as fake or real, despite the complexities of language, nuances of context, and the evolving nature of online discourse, all while addressing issues of class imbalance and adversarial attacks.

1.3 OBJECTIVE OF THE PROJECT

Developing an accurate and reliable system to identify and classify fake statements is crucial in today's digital age. The primary goal is to design and implement a natural language processing (NLP) based model that can effectively distinguish between factual and fabricated information, thereby promoting media literacy, critical thinking, and informed decision-making.

II. LITERATURE SURVEY

M.Granik et al., presented an approach for fake news detection using naive Bayes classifier. This approach was implemented as a software system and tested against a data set of Facebook news posts. We achieved classification accuracy of approximately 74% on the test set which is a decent result considering the relative simplicity of the model. This results may be improved in several ways that are described in the article as well. Received results suggest, that fake news detection problem can be addressed with artificial intelligence methods. The news information can be easily accessed through Internet and social media. It is convenient for user to follow their interest events available in online mode. Mass-media playing a huge role in influencing the society and as it is common, some people try to take advantage of it. Sometimes mass media modulate the information in their own way to reach their goal. There are many websites which provide false information. They consciously try to bring out propaganda, hoaxes and misinformation under the guise of being authentic news.

The exhaustivity of document descriptions and the specificity of index terms are usually regarded as independent. It is suggested that specificity should be interpreted statistically, as a function of term use rather than of term meaning. The effects on retrieval of variations in term specificity are examined, experiments with three test collections showing, in particular, that frequently-occurring terms are required for good overall performance. It is argued that terms should be weighted according to collection frequency, so that matches on less frequent, more specific, terms are of greater value

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

than matches on frequent terms. Results for the test collections show that considerable improvements in performance are obtained with this very simple procedure We are familiar with the notions of exhaustivity and specificity: exhaustivity is a property of index descriptions, and specificity one of index terms. They are most clearly illustrated by a simple keyword or descriptor system. In this case the exhaustivity of a document description is the coverage of its various topics given by the terms assigned to it; and the specificity of an individual term is the level of detail at which a given concept is represented. These features of a document retrieval system have been discussed by Cleverdon et al. (1966) and Lancaster (1968), For instance, if the exhaustivity of a document description is increased by the assignment of more terms, when the number of terms in the indexing vocabulary is constant, the chance of the document matching a request is increased. Sparck Jones, K proposed an idea of an optimum level of indexing exhaustivity for a given document collection then follows: the average number of descriptors per document should be adjusted so that, hopefully, the chances of requests matching relevant documents are maximized, while too many false drops are avoided. Exhaustivity obviously applies to requests too, and one function of a search strategy is to vary request exhaustivity. I will be mainly concerned here, however, with document description.

L.Timchenko et al., presented a method of parallel-hierarchical transformations for rapid recognition of dynamic images using GPU technology. Direct parallel-hierarchical transformations based on cluster CPU-and GPU-oriented hardware platform. Mathematic models of training of the parallel hierarchical (PH) network for the transformation are developed, as well as a training method of the PH network for recognition of dynamic images. This research is most topical for problems on organizing high-performance computations of super large arrays of information designed to implement multi-stage sensing and processing as well as compaction and recognition of data in the informational structures and computer devices. This method has such advantages as high performance through the use of recent advances in parallelization, possibility to work with images of ultra dimension, ease of scaling in case of changing the number of nodes in the cluster, auto scan of local network to detect compute node.

III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The news information that we get is not always true. Paradoxically, the Internet makes it harder to fact-check the available information, because there are too many sources that often even contradict each other. All of this caused the emergence of fake news. Mass media and social media have a great influence on a public. There are sides that are interested in using this to achieve their political goals with the help of fake news. They provide false information in form of news to manipulate people in different ways. There exist lots of websites with a single purpose of spreading of false information. They publish fake news, propaganda materials, hoaxes, conspiracy theories in disguise of a real news information.

3.1.2 DISADVANTAGES OF EXISTING SYSTEM

- The main purpose of fake news websites is to affect the public opinion on certain matters (mostly political). Examples of this may be found in Ukraine, United States of America, Great Britain, Russia and many other countries. Thus, fake news is a global issue and an important challenge to tackle.
- This cause by the rise of deep learning and other artificial intelligence techniques showed us that they can be very effective in solving complex, sometimes even non-formal classification tasks.

3.2 PROPOSED SYSTEM

First of all it was decided to use only the statements themselves for classification purposes. This means that none of the metadata provided is used for classification. The classification algorithm might actually be improved in the future by taking into account this metadata. Splitting the statements into separate tokens (words). Removing all numbers. Removing all punctuation marks. Remove all other non-alpha characters Applying the stemming procedure to the rest of the tokens. In linguistic morphology and information retrieval, stemming (or lemmatization) is the process of reducing inflected or derived words to their word stem, base or root form – generally a written word form. This helps to treat similar words (like “write” and “writing”) as the same words and might be extremely helpful for classification purposes.

3.2.1 ADVANTAGES OF PROPOSED SYSTEM

- Stop words are the words occur in basically all types of texts. These words are common and they do not really affect the meaning of the textual information.
- Term frequency–inverse document frequency is a numerical statistic measure reflects the importance of a certain word to a document in a collection or corpus

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

3.3MODULES

In this work we include four modules are used,

- Data Pre-Processing
- Classification with logistic regression
- Classification with naive Bayes classifier
- Classification with support vector machines

3.2.1 DATA PRE-PROCESSING

Before actually applying the artificial intelligence algorithms to the data, it should be pre-processed. First of all it was decided to use only the statements themselves for classification purposes. This means that none of the metadata provided is used for classification. The classification algorithm might actually be improved in the future by taking into account this metadata

3.2.2 CLASSIFICATION WITH LOGISTIC REGRESSION

Logistic regression is a statistical method for analyzing a data set in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). For the cases when there are more than two labels, the strategy, which is called "One versus all", is used. In this strategy every category is binary classified against its inverse (a fictional category that states that the example does not belong to the current category). The category with the highest score is picked as a result of a classification.

3.2.3 CLASSIFICATION WITH NAIVE BAYES CLASSIFIER

In artificial intelligence, naive Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes theorem with strong (naive) independence assumptions between the features. Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. It is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable.

3.2.4 CLASSIFICATION WITH SUPPORT VECTOR MACHINES

In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. A support vector machine model is a representation of the examples as points in space mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In the classification tasks for the cases when there are more than two labels, "One versus all" strategy is used.

IV. SYSTEM DESIGN

4.1 System architecture

The system architecture is shown in figure 1.

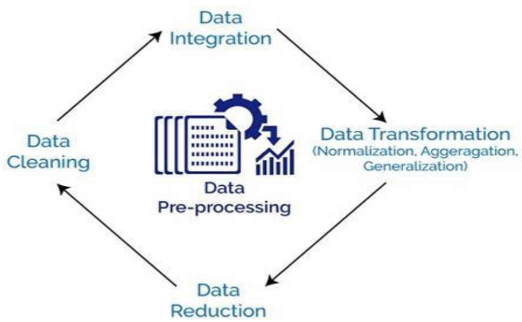


Fig 1 System Architecture

4.2 DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

The data flow diagram is shown in figure 2.

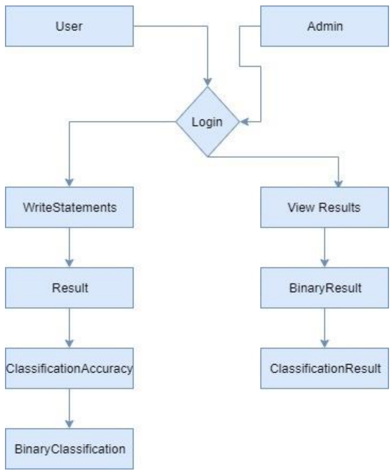


Fig 2: data flow diagram

4.3 ALGORITHMS

4.3.1 NATURAL LANGUAGE PROCESSING

Natural Language Processing (NLP) is a branch of artificial intelligence (AI) that enables computers to understand, interpret, and generate human language. NLP combines linguistics and computer science to process and analyze large amounts of natural language data, such as text or speech.

The primary goal of NLP is to bridge the gap between human communication and computer understanding. It is widely used in applications like chatbots, sentiment analysis, language translation, speech recognition, and text classification (including fake statement classification).

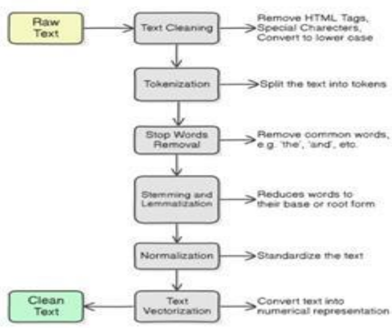


Fig 3. NLP (Natural Language Processing)

Key Terminologies in NLP

- **Tokenization:**. The process of breaking down text into smaller units called tokens (words or phrases).
- **Stemming:** Reducing words to their root or base form. (Example: "Playing", "Played", and "Plays" are reduced to "Play")
- **Stop Words:** Common words (like "is", "the", "and") that are usually removed during preprocessing as they do not

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

add much meaning.

- **Bag of Words (BoW):** Represents text as a set of words and their frequency, ignoring grammar and word order.
- **TF-IDF (Term Frequency - Inverse Document Frequency):** A numerical statistic to reflect how important a word is to a document in a collection.
- **Text Classification :** Categorizing text into predefined classes (e.g., True, Flase).

Working of NLP:

The process begins with data pre-processing, where raw text is cleaned and prepared. This includes tokenization (breaking text into individual words or sentences), removing stop words (common but insignificant words like "the" or "is"), and stemming or lemmatization (reducing words to their root forms). After pre-processing, feature extraction methods like Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), or word embeddings (such as Word2Vec and GloVe) are applied to convert text into numerical vectors that machine learning models can understand.

Once the text data is transformed into vectors, machine learning or deep learning algorithms are employed to perform tasks like classification, sentiment analysis, or language translation. Traditional algorithms such as Logistic Regression, Naive Bayes, and Support Vector Machines (SVM) are commonly used for basic text classification. After training, models are evaluated using metrics like accuracy, precision, recall, and F1 score to assess performance. NLP applications are vast, ranging from sentiment analysis and chatbot development to fake news detection and language translation.

4.3.2 LOGISTIC REGRESSION

Logistic Regression is a widely used supervised learning algorithm that is particularly effective for binary classification tasks. In the context of fake statement classification, Logistic Regression models the probability that a given statement belongs to one of two categories: True or Flase. This algorithm is chosen for its simplicity, interpretability, and effectiveness when dealing with linearly separable data.

The fundamental idea behind Logistic Regression is to find a linear combination of input features that can predict the log-odds of the target class. Unlike linear regression, which predicts continuous values, Logistic Regression uses the sigmoid function to map predicted values to probabilities between 0 and 1.

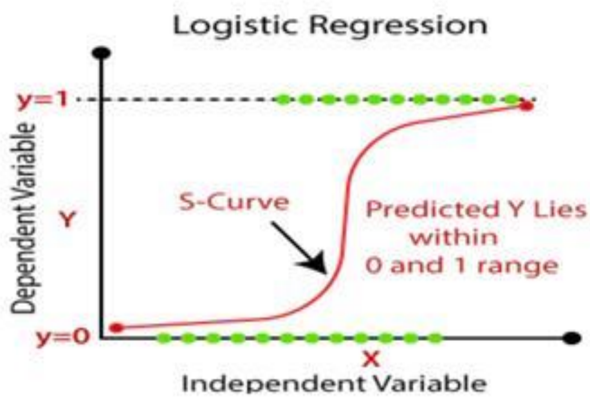


Fig 4. Logistic Regression

Therefore, to calculate RMSE, the formula is as follows:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

Here, z is the linear combination of input features ($z=\beta 0+\beta 1x1+\beta 2x2+\cdots+\beta nxn$), where $\beta 0$ is the intercept, βi are the coefficients, and xi are the input features extracted from textual data.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

4.3.3 SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine (SVM) is a powerful supervised learning algorithm commonly used for binary classification tasks, including fake statement classification. SVM works by finding an optimal hyperplane that best separates the data points of different classes. In the context of fake statement classification, the goal is to differentiate between fake and real statements based on textual features.

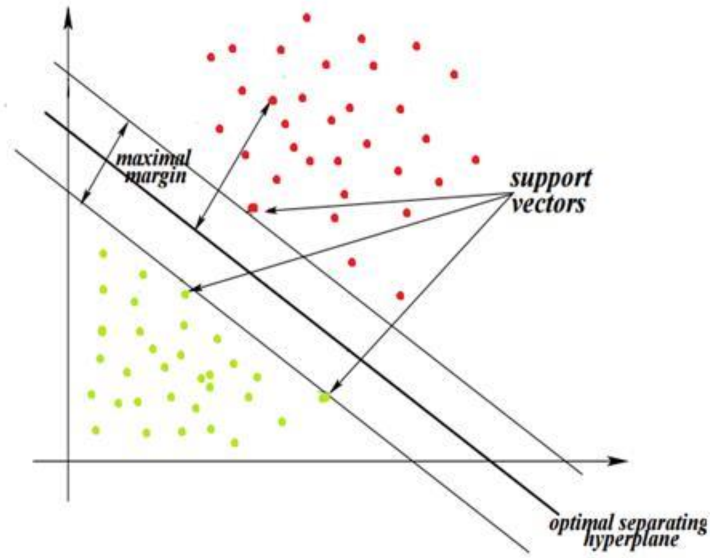


Fig 5: Support Vector Machine

To classify fake news, textual data is first preprocessed by cleaning, tokenizing, removing stopwords, and performing stemming or lemmatization. The cleaned text is then vectorized using techniques like **TF-IDF** or **Word Embeddings** to convert it into numerical features. These features are fed into the SVM model, which learns the pattern of fake and real news by optimizing the hyperplane parameters. The trained model is then evaluated using metrics such as **accuracy**, **precision**, **recall**, and **F1-score** to ensure reliable performance. SVM's ability to handle high-dimensional data and its robustness against overfitting make it an effective choice for fake news classification.

V. RESULTS

The following figures present the sequence of screenshots of the results.

Fig 6a: In above screen click on 'Register' to Register

Fig 6b: Registration page

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

Fig 6c: login page

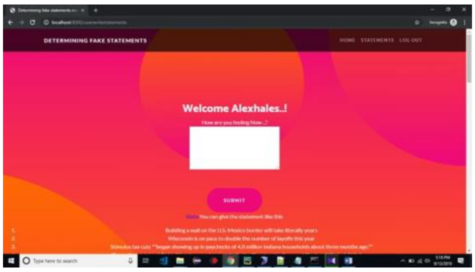


Fig 6d: Give Public Statement and click on submit button.

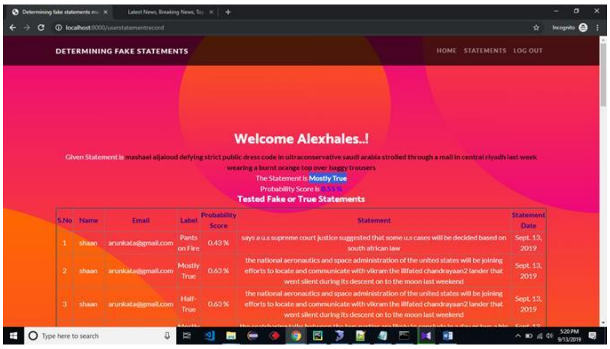


Fig 6e: The Result for User statements is shown here.

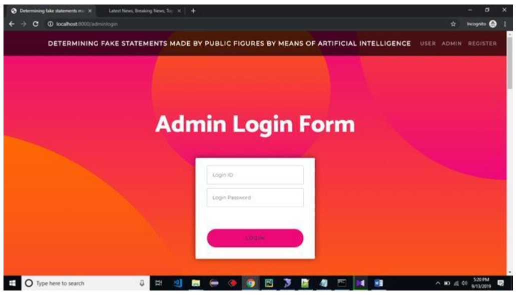


Fig 6f: Admin can login with valide Email amd Password

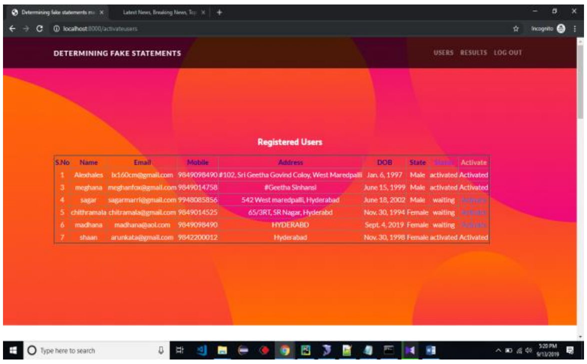


Fig 6g: In the above screen admin can activate users by clicking 'Activate'.

VI. CONCLUSIONS AND FUTURE WORK

6.1 CONLUSIONS

In this paper, several algorithms for classifying statements made by public figures were implemented unsurprisingly, deep neural networks showed the best results both in classification accuracy based on six categories and binary classification. This encourages future research with extensive usage of deep neural networks. Achieved results might be significantly improved. It is possible to both improve the data which is used for training as well as the machine learning models themselves. This might be a subject for future research. Together with the text summarization (the problem that also can be solved by means of artificial intelligence), this approach might be used for classification of news articles as fake or true. This might also be a subject for future research.

6.2 FUTURE WORK

In the future, this project can be extended by using more advanced machine learning and deep learning techniques such as LSTM or transformer-based models like BERT. These models can better understand the context of a statement and may provide more accurate results. The current project focuses mainly on the text content of statements, but future versions could also include metadata such as the speaker's identity, party affiliation, or subject category to improve prediction quality.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 2, March-April 2025 ||

DOI:10.15680/IJARETY.2025.1202045

Another possible improvement is the development of a real-time fake statement detection system, such as a web tool or browser extension. This system could analyze live data and warn users about potentially fake content. Additionally, expanding the dataset with newer and more diverse examples, or including support for multiple languages, would make the model more useful in real-world applications. These improvements could help make fake news detection more reliable, accessible, and applicable on a global scale.

REFERENCES

[1] M. Granik,V. Mesyura, “Fake newe detection using naive bayes classifier,”2017 IEEE First Ukraine Conference on Electrical and Computer Engineering(UKRCON),Kiev,2017,pp,900-903.
[2] Cade Metz. (2016, Dec. 16). "The bittersweet sweepstakes to build an AI that destroys fake news". Available: https://www.wired.com/2016/12/bittersweet-sweepstakes-build-aidestroys- fake-news/
[3] Fake news RAMP: classify statements of public figures. (n.d.) [Online]. Available: https://www.ramp.studio/problems/fake_news
[4] The Principles of the Truth-O-Meter: PolitiFact’s methodology for independent fact-checking.(2018, Feb. 12) http://www.politifact.com/truth-o-meter/article/2018/feb/12/principlestruth- o-meter-politifacts-methodology-i/. Accessed Mar. 24, 2018.
[5] Rajaraman, A.; Ullman, J. D. "Data Mining". (2011) Available: http://i.stanford.edu/~ullman/mmds/ch1.pdf. Accessed Mar. 24, 2018.
[6] Muniraju Hullurappa, Mohanarajesh Kommineni, “Integrating Blue-Green Infrastructure Into Urban Development: A Data-Driven Approach Using AI-Enhanced ETL Systems,” in Integrating Blue-Green Infrastructure Into Urban Development, IGI Global, USA, pp. 373-396, 2025.
[7] Stemming and lemmatization. (n.d.) Available: https://nlp.stanford.edu/IR-book/html/htmledition/stemming-andlemmatization- 1.html. Accessed Mar. 24, 2018
[8] Sparck Jones, K. (1972). "A Statistical Interpretation of Term Specificity and Its Application in Retrieval". Journal of Documentation, vol 28, pp 11–21.
[9] David A. Freedman (2009). “Statistical Models: Theory and Practice”. Cambridge University Press. p. 128.
[10] Ho, Tin Kam (1995). “Random Decision Forests”. Proceedings of the 3rd International Conference on Document Analysis and Recognition, Montreal, QC, 14–16 August 1995. pp. 278–282.
[11] Cortes, Corinna; Vapnik, Vladimir N. (1995). "Support-vector networks". Machine Learning, vol 20, pp 273–297.
[12] Artificial Neural Networks as Models of Neural Information Processing. Frontiers Research Topic (n.d.). https://www.frontiersin.org/researchtopics/4817/artificial-neural-networks-as-models-of-neural-informationprocessing. Accessed Mar. 24, 2018.
[13] Opitz, D.; Maclin, R. (1999). "Popular ensemble methods: An empirical study". Journal of Artificial Intelligence Research. 11: 169.
[14] A. Yarovyi, L. Timchenko, et al., "Parallel-hierarchical processing and classification of laser beam profile images based on the GPU-oriented architecture", Proc. SPIE 10445, Photonics Applications in Astronomy, Communications, Industry, and High Energy Physics Experiments 2017, 104450R (7 August 2017); doi: 10.1117/12.2280975.
[15] L. Timchenko, A. Yarovyi, et al.,"The method of parallel-hierarchical transformation for rapid recognition of dynamic images using GPGPU technology", Proc. SPIE 10031, Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2016.

IJARETY

INNO SPACE
SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

www.ijarety.in editor.ijarety@gmail.com