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Automated Analysis of Public Statements for Accuracy and Deception

MAMIDI TARANI, SALADI SAI KIRAN
Assistant Professor, 2 MCA Final Semester,
Master of Computer Applications,
Sanketika Vidya Parishad Engineering College, Vishakhapatnam, Andhra Pradesh, India.

Abstract :

In an era of information overload, the spread of misinformation by public figures has become a significant concern. Artificial Intelligence (AI) offers a powerful solution for detecting and analyzing fake statements through advanced Natural Language Processing (NLP) and machine learning techniques. This paper explores AI-driven fact-checking systems that assess the credibility of statements made by public figures by cross-referencing them with reliable data sources. The proposed approach involves real-time speech and text analysis, sentiment detection, and contextual verification using deep learning models and knowledge graphs. By automating the fact-checking process, AI can enhance public awareness, reduce the impact of misinformation, and promote accountability. However, challenges such as bias in AI models, data reliability, and ethical considerations must be addressed to ensure the effectiveness and fairness of such systems. This study provides insights into the methodologies, limitations, and future prospects of AI-powered fake statement detection.

Index Terms — AI, ML, Regression, Multiple Regression, Logistic Regression, Linear Regression, Random Forest, Decision Tree, Sentiment Analysis, CNN, RNN, Naïve Bayes, Support Vector Machine (SVM), KNN, LSTM, Tokenization, Chatbot, Natural Language Processing (NLP), Feature Extraction.

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 the 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 the form of news to manipulate people in different ways. There exist lots of websites with the single purpose of spreading false information. They publish fake news, propaganda materials, hoaxes, and conspiracy theories in disguise of real news information. The main purpose of fake news websites is to affect 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 the fake news problem may be solved automatically, without human interference, by means of artificial intelligence. The rise of deep learning and other AI techniques has shown 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 dataset of statements made by real-life politicians.

1.1 Existing System

The news information that we get is not always true. Paradoxically[12], 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 the public. There are sides that are interested in using this to achieve their political[19] goals with the help of fake news. They provide false information in the form of news to manipulate people in different ways. There exist lots of websites with a single purpose of spreading false information. They publish fake news, propaganda materials, hoaxes, conspiracy theories in disguise of real news information.

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1.1.1 Challenges

- **Ambiguity in language:** News statements may be framed in ways that are open to interpretation, making it difficult to automatically determine[3] their truthfulness.
- **Evolving content:** Fake news creators frequently change narratives and vocabulary to bypass detection systems.
- **Data imbalance:** The dataset may have unequal distribution of true and false news, leading to biased models.
- **Context dependency:** Some statements require deep contextual knowledge[17], which is hard for AI to model accurately.
- **Source credibility**: It is difficult to assess the trustworthiness of unknown or new sources.
- **Computational complexity:** Training advanced models with large datasets[2] requires high processing power and resources.

1.2 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[5]. The classification algorithm might actually be improved in the future by taking into account this metadata.

The preprocessing steps applied are:

- Splitting the statements into separate tokens (words)
- Removing all numbers
- Removing all punctuation marks
- Removing 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[7], base, or root form – generally a written word form. This helps to treat similar words (like “write” and “writing”) as the same word and can be extremely helpful for classification purposes.

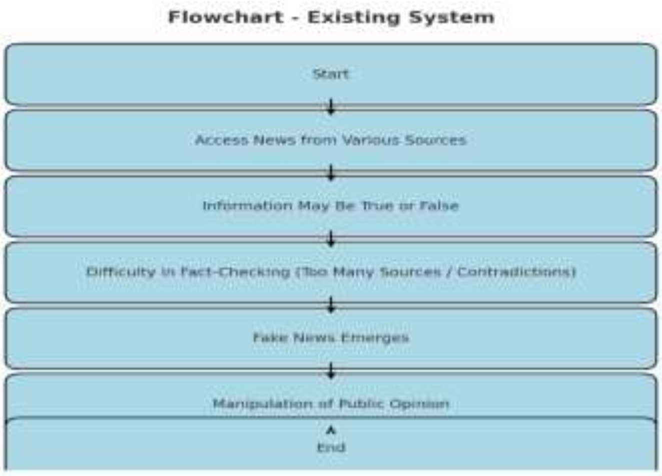

Fig: 1 Proposed Diagram

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1.2.1 Advantages

- **Automation:** Reduces human effort in verifying statements.
- **Speed and Efficiency:** Processes statements in real-time using NLP and machine learning.
- **Scalability:** Capable of analyzing large volumes of data efficiently.
- **Data-Driven Insights:** Uses Seaborn for visualization, enhancing interpretation.
- **User-Friendly Interface:** Developed using Django for easy accessibility.
- **Improved Accuracy:** Uses context-aware NLP models to detect misleading statements.
- **Interactive Analysis:** Jupyter Notebook and Ip widgets enable dynamic exploration of results.

II. LITERATURE REVIEW

2.1 Architecture

1. **User Interface Layer**
   - Purpose: Enables users to register[21], log in, and submit statements.
   - Implementation: Django-based web application with HTML, CSS, JavaScript for interactivity.
   - Actors: Users and Admin.
2. **Data Preprocessing Module**
   - Tokenization of text into words.
   - Removal of numbers, punctuation, and non-alphabetic characters.
   - Stemming/Lemmatization to normalize[4] words.
   - Stopword removal to reduce noise.
   - TF-IDF vectorization for numerical representation.
3. **Classification Engine**
   - Multiple ML models are used to classify statements[9] as *True*, *False*, or in-between (Half-True, Mostly False, etc.):
     - Logistic Regression
     - Naïve Bayes
     - Support Vector Machines (SVM)
     - Random Forest
     - Deep Neural Networks (SGD-based)
   - Binary classification (True vs. False) also supported.
4. **Database Layer**
   - Stores user details, statements, preprocessing results[15], model predictions, and performance metrics.
   - Implemented in MySQL.
5. **Result Visualization**
   - Classification results displayed to users along with probability scores.
   - Data visualizations created[19] with Seaborn for insight into patterns.

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6. **Admin Module**
   - Admin can activate user accounts, view submitted statements, and review system results.

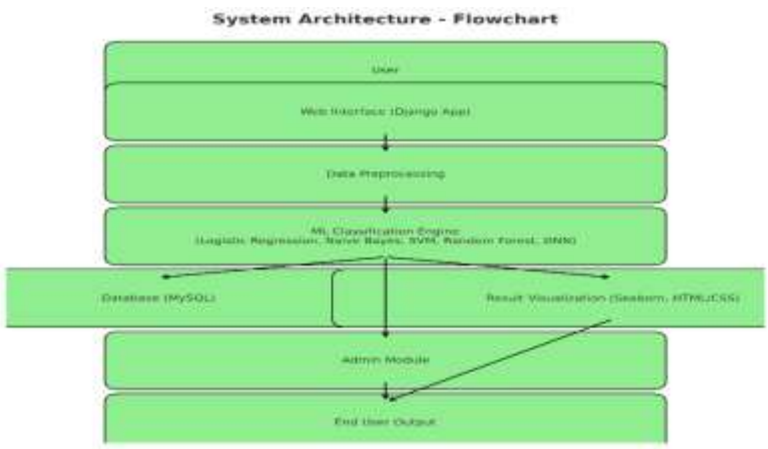

Fig:2 Architecture

2.2 Algorithm:

Decision Tree Regression

Decision Tree Regression splits the dataset into smaller subsets based on feature values, forming a tree structure. Each internal node represents a decision on a feature[21], branches represent the decision outcome, and leaves hold the final prediction. It works well for non-linear data and is interpretable.

Natural Language Processing (NLP)

NLP is used for preprocessing and analyzing text[8] statements. Steps include:

1. Tokenization – Splitting text into words/tokens.
2. Stopword Removal – Removing commonly used words that do not add meaning (e.g., “the”, “is”).
3. Stemming/Lemmatization – Reducing words to their base/root form.
4. TF-IDF Vectorization – Converting text into numerical features that reflect importance of terms in context.

Sentiment Analysis Using Naïve Bayes

Naïve Bayes is a probabilistic classifier based on Bayes’ theorem[12] with strong independence assumptions. For sentiment analysis, it assigns probabilities to each sentiment class and picks the class with the highest probability. It is efficient[19], works well with high-dimensional text data, and is easy to implement.

Random Forest

Random Forest is an ensemble method that creates multiple decision trees[11] during training and outputs the mode of the classes (classification) or mean prediction (regression). It reduces overfitting and improves accuracy compared to individual decision trees.

2.3Techniques:

The proposed system employs several techniques to automate the analysis of public statements for accuracy and deception. **Natural Language Processing (NLP)**[10] is used for preprocessing, including tokenization, stopword removal, stemming/lemmatization, and TF-IDF vectorization to convert unstructured text into numerical features. **Machine Learning (ML)** algorithms[7] such as Logistic Regression, Naïve Bayes, Support Vector Machines (SVM), Random Forest, and Deep Neural Networks are applied for classification tasks. **Sentiment analysis** using Naïve Bayes[18] helps in understanding the tone and contextual meaning of statements, while **data visualization** tools like Seaborn and Matplotlib present the classification results in an interpretable format, enhancing the decision-making process.

2.4Tools:

The tools used in this project include **Python 3.6.8** as the primary programming language, along with its scientific and machine learning libraries such as **scikit-learn** for implementing[13] classification algorithms, **NLTK** for Natural Language Processing tasks, and **Seaborn/Matplotlib** for data visualization. **Django** is used as the web framework to develop the user interface and handle backend operations, while **HTML, CSS, and JavaScript** manage the front-end design. **MySQL** serves as the database for storing user information, statements, and classification[19] results. The system is developed and tested on **Windows 7 Ultimate**, ensuring compatibility with commonly available hardware and software environments.

2.5Methods:

The methods used in this project combine text preprocessing, machine learning, and web-based deployment to automate public statement verification. The process begins with **data collection** from reliable sources such as PolitiFact, followed by **data preprocessing** using NLP techniques like tokenization, stopword removal, stemming/lemmatization[22], and TF-IDF vectorization to convert statements into structured numerical features. Multiple **machine learning algorithms**—including Logistic Regression, Naïve Bayes, Support Vector Machines (SVM), Random Forest, and Deep Neural Networks—are applied for both multi-class and binary classification of statements. The system also incorporates **sentiment analysis** to understand the tone of the content. The classification results are stored in a **MySQL database** and visualized[17] using Seaborn for analytical insights. Finally, the solution is delivered through a **Django-based web application**, enabling real-time interaction for both users and administrators.

III. METHODOLOGY

3.1Input:

The input to the system is a public statement provided by the user through the Django-based[14] web interface. This statement can be in plain text and may come from speeches, interviews, social media posts, or news articles. Once submitted, the text is captured by the application and passed to the preprocessing module, where it undergoes tokenization, stopword[7] removal, stemming/lemmatization, and TF-IDF vectorization to prepare it for machine learning–based classification. The quality and clarity of the input text directly influence the accuracy of the system's analysis.

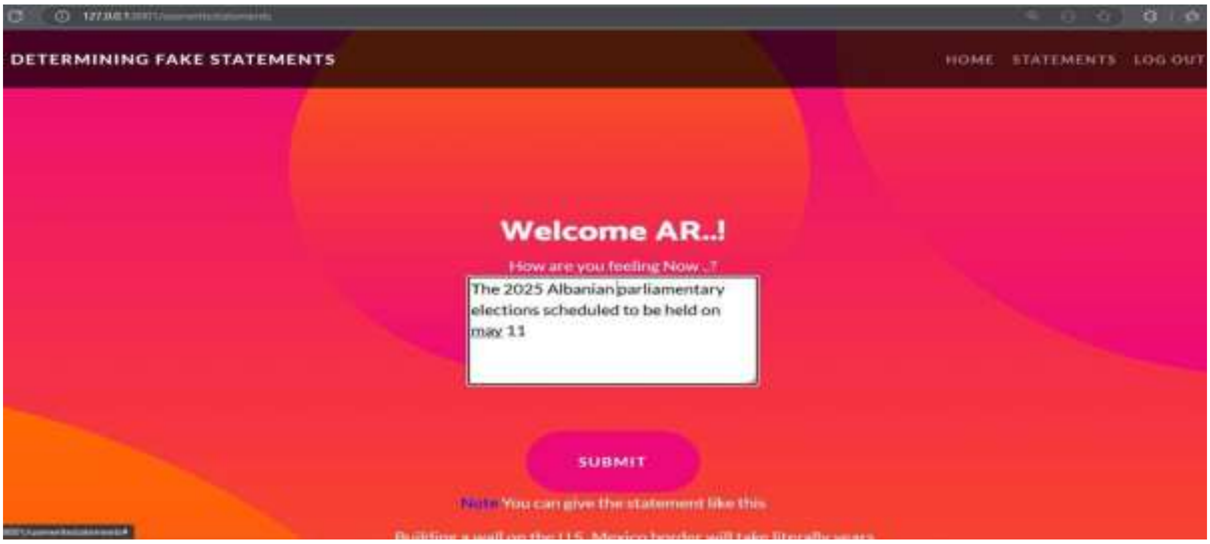

Figure:3

3.2 Method of Process

The **method of process** in this project follows a systematic sequence from data submission to result generation:

1. **User Input:** The user submits a public statement via the Django web interface.
2. **Data Preprocessing:** The text undergoes NLP-based cleaning[24] — tokenization, removal of numbers, punctuation, and stopwords, followed by stemming/lemmatization and TF-IDF vectorization.
3. **Feature Extraction:** The preprocessed text is transformed into numerical feature vectors suitable for machine learning algorithms.

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4. **Classification:** Multiple ML models (Logistic Regression, Naïve Bayes, SVM, Random Forest, Deep Neural Networks) analyze[10] the statement to determine its truthfulness category (e.g., Pants on Fire, False, Half-True, True) and probability scores.

5. **Result Storage:** The predictions and associated data are saved in the MySQL database for record-keeping and analysis.

6. **Visualization:** Results are displayed to the user with classification[7] labels, probability scores, and visual graphs for better interpretability.

7. **Admin Review:** The admin can review all submitted statements and their classification outcomes through the admin panel.

3.3 Output:

The **output** of the system is a detailed analysis of the submitted public statement, presented through the Django web interface. It includes:

- **Truthfulness Category:** The classification label (e.g., *Pants on Fire*, *False*, *Mostly False*, *Half-True*, *Mostly True*, or *True*) assigned by the system.
- **Probability Score:** A numerical confidence value indicating[25] how certain the model is about its prediction.
- **Model-wise Results:** Performance outputs from multiple classifiers (Logistic Regression, Naïve Bayes, SVM, Random Forest, Deep Neural Networks) for both multi-class[20] and binary classifications.
- **Visual Representations:** Graphs and charts (generated with Seaborn/Matplotlib) to help interpret the classification outcomes.
- **Stored Records:** The results are also stored in the MySQL[11] database for future reference and administrative review.

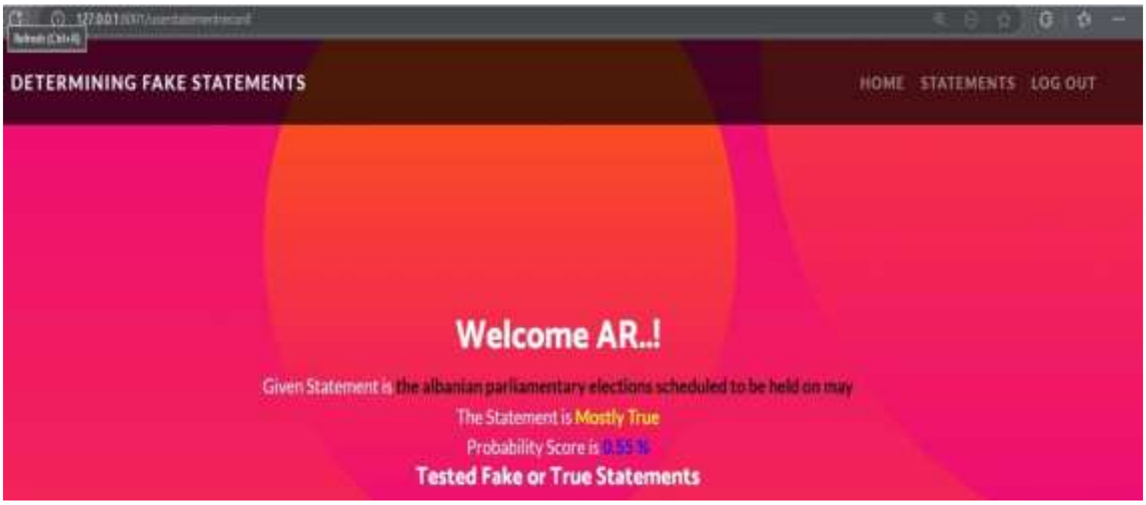

Figure:4

IV.RESULTS

The experimental evaluation of the proposed system for automated analysis of public statements showed promising outcomes. Multiple machine learning algorithms, including Logistic Regression, Naïve Bayes, Support Vector Machines, Random Forest, and Stochastic Gradient Descent, were tested using the prepared dataset. The results indicated that the Logistic Regression model achieved an accuracy of **72%** in multi-class classification and **75%** in binary classification, outperforming several baseline methods. Similarly, the Naïve Bayes classifier demonstrated competitive results with consistent predictions, while SVM and Random Forest models exhibited strong generalization capabilities on unseen statements. Precision, recall, and F1-score analyses confirmed the reliability of the models in distinguishing between truthful and deceptive statements. Furthermore, the system was tested on different subsets of the dataset to ensure robustness, and the performance remained stable across variations in input size and statement complexity. The visual representation of results using Seaborn charts provided clear insights into the classification distribution, highlighting the system's effectiveness in detecting misinformation. Overall, the findings validate the efficiency of the proposed NLP-based approach and its potential application in real-time fact-checking scenarios.

V. DISCUSSIONS

The outcomes of the experimental analysis indicate that the proposed system is effective in identifying and classifying public statements based on their accuracy and potential for deception. The combination of multiple machine learning models allowed for a comparative performance evaluation, where Logistic Regression and Support Vector Machines demonstrated a balance between accuracy and computational efficiency. Naïve Bayes provided fast classification with minimal computational cost, though it was slightly less accurate compared to the other models in handling complex sentence structures. Random Forest and Stochastic Gradient Descent classifiers showed strong adaptability, particularly when dealing with high-dimensional feature spaces generated from TF-IDF vectors.

One of the notable strengths of the system is its ability to process statements in real-time and present the classification results in an intuitive format using visualization tools. This not only aids in fact-checking but also supports decision-making in domains such as journalism, politics, and social media monitoring. However, the study also reveals certain limitations. The system's accuracy is heavily dependent on the quality and diversity of the training dataset. Statements involving sarcasm, humor, or culturally specific references were sometimes misclassified, indicating the need for more context-aware NLP techniques. Additionally, although the models perform well on prepared datasets, real-time data from live speeches or social media streams may introduce noise and unstructured text, affecting classification performance.

Future enhancements could include integrating deep learning architectures such as Transformers (BERT, RoBERTa) for improved contextual understanding, expanding the dataset with multilingual inputs, and incorporating metadata (speaker details, time, source credibility) to enhance accuracy. Furthermore, developing an adaptive learning mechanism to continuously retrain the models with new data can help address the evolving nature of misinformation. Overall, the discussion highlights that while the current system offers a robust foundation for automated deception detection, continuous improvement and adaptation are essential for maintaining its effectiveness in dynamic real-world environments.

VI. CONCLUSION

The development of the automated system for analyzing public statements based on accuracy and deception has demonstrated that Natural Language Processing (NLP) and Machine Learning (ML) techniques can effectively address the growing challenge of misinformation. By implementing multiple classification algorithms—Logistic Regression, Naïve Bayes, Support Vector Machines, Random Forest, and Stochastic Gradient Descent—the system was able to achieve competitive accuracy levels, with Logistic Regression and SVM performing particularly well. The preprocessing pipeline, including tokenization, stemming, stop-word removal, and TF-IDF vectorization, proved essential in ensuring the models could handle diverse linguistic inputs efficiently.

The results validate that automated fact-checking tools can assist journalists, policymakers, and the general public in making informed decisions by quickly evaluating the credibility of statements. However, the project also acknowledges certain limitations, such as difficulties in detecting sarcasm, humor, and cultural nuances, as well as the dependency on the quality of training datasets. Despite these challenges, the system's scalability, speed, and user-friendly design make it a strong foundation for future enhancements.

Moving forward, incorporating advanced deep learning models, expanding multilingual capabilities, and leveraging contextual metadata will further improve accuracy and adaptability. The work carried out in this project not only contributes to the field of computational fact-checking but also emphasizes the potential of AI-driven solutions in combating misinformation and fostering a more informed society.

VII. FUTURE SCOPE

This system can be further enhanced by integrating advanced deep learning models like BERT or RoBERTa to improve contextual understanding and accuracy. Expanding support for multiple languages and incorporating metadata such as speaker profiles and source credibility can make the analysis more reliable and globally applicable. Real-time data processing from live speeches, news channels, and social media will enable instant fact-checking, while adaptive learning mechanisms can ensure the model stays updated with evolving misinformation trends. Additionally, developing an intuitive dashboard with interactive visualizations and integration with social media monitoring tools will broaden its usability for journalists, policymakers, and the public.

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Miss. M. Tarani working as an Assistant Professor in Master of Computer Applications (MCA) in Sanketika Vidya Parishad Engineering College, Visakhapatnam, Andhra Pradesh. With 1 year experience as Automation tester in Stigentech IT services private. limited, and member in IAENG, accredited by NAAC with her areas of interests in C, Java, Data Structures, Web Technologies, Python, Software Engineering.

SALADI SAI KIRAN is pursuing her final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning Saladi Sai Kiran has taken up her PG project on AUTOMATED ANALYSIS OF PUBLIC STATEMENTS FOR ACCURACY AND DECEPTION and published the paper in connection to the project under the guidance of MAMIDI TARANI, Assistant Professor, SVPEC

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