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FAKE NEWS DETECTION USING ML

BY

BIJAYA RAJ PANT

A PROJECT REPORT

SUBMITTED TO THE DEPARTMENT OF BACHELOR OF COMPUTER APPLICATION

IN FULFILLMENT OF THE REQUIREMENT FOR

THE DEGREE OF BACHELOR OF COMPUTER APPLICATION

DEPARTMENT OF BACHELOR OF COMPUTER APPLICATION LALITPUR, NEPAL

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2022-1-53-0156

Project Supervisor

Er. Nishan Khanal

A project submitted in fulfillment of the requirements for the degree of

Bachelor of Computer Application

Department of Bachelor of Computer Application

Pokhara University, Citizen College

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DECLARATION

I declare that the work hereby submitted for Bachelor of Computer Application at the Pokhara University, Citizen College entitled "**FAKE NEWS DETECTION USING ML**" is my own work and has not been previously submitted by me at any university for any academic award. I authorize the Pokhara University, Citizen College to lend this project work to other institutions or individuals for the purpose of scholarly research.

BIJAYA RAJ PANT
2022-1-53-0156
JULY, 2025

RECOMMENDATION

The undersigned certify that they have read and recommend to the Department of Bachelor of Computer Application for acceptance, a project work entitled "**FAKE NEWS DETECTION USING ML**", submitted by **BIJAYA RAJ PANT** in fulfillment of the requirement for the award of the degree of "**Bachelor of Computer Application**".

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JULY, 2025

DEPARTMENTAL ACCEPTANCE

The project work entitled "**FAKE NEWS DETECTION USING ML**", submitted by **BIJAYA RAJ PANT** in fulfillment of the requirement for the award of the degree of "**Bachelor of Computer Application**" has been accepted as a genuine record of work independently carried out by the student in the department.

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JULY, 2025

LETTER OF APPROVAL

We certify that we have examined this report entitled "**FAKE NEWS DETECTION USING ML**", and are satisfied with the **BIJAYA RAJ PANT's** Project III. In our opinion, it is satisfactory in the scope and qualifies as a project work in fulfillment of the requirements for the **Bachelor of Computer Application** under **Department of Bachelor of Computer Application, Pokhara University**.

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ABSTRACT

The Fake News Detection System represents a significant step forward in the field of digital media verification, providing a reliable and intelligent solution for identifying misleading or false news content. Utilizing the power of Machine Learning and by cross-checking internet sources, this project offers a robust framework capable of analyzing textual news articles and classifying them as real or fake with high accuracy. The system is designed with a focus on simplicity, scalability, and real-world applicability, making it suitable for both academic and practical use cases. At the core the system lies a Logistic Regression model, trained on a well-curated dataset containing real and fake news articles from diverse topics. The model employs Natural Language Processing (NLP) techniques such as TF-IDF vectorization to extract meaningful features from raw text. Users interact with the system via a web interface, where they can input a news headline or body and receive immediate feedback on its authenticity. This project not only delivers fast and accurate predictions but also addresses the growing threat of misinformation in digital media. With its user-friendly design, strong technical foundation, and educational value, the Fake News Detection System empowers users to make informed decisions and promotes trust in online information sources. this machine learning-based system provides a practical and efficient approach against fake news. Through intelligent automation and accessible design, it demonstrates how technology can be leveraged to support truth and transparency in the modern information landscape.

Keywords: ***Fake News, Logistic Regression, Machine Learning, Natural Language Processing.***

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LIST OF ABBREVIATIONS

APIs	Application Programming Interfaces
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional Neural Network
CSS	Cascading Stylesheet
CSV	Comma-Separated Values
DL	Deep Learning
GB	Giga Byte
HTML	Hypertext Markup Language
i5	Intel Core i5 Processor
IDF	Inverse Document Frequency
LIAR	Labeled Information for Automated Recognition
ML	Machine Learning
NV	Naive Bayes
NLP	Natural Language Processing
OTP	One Time Password
RAM	Random Access Memory
RNN	Recurrent Neural Networks
SSD	Solid State Drive
SVM	Support Vector Machine
TF	Term-Frequency
TF-IDF	Term Frequency–Inverse Document Frequency
UI	User Interface
VS Code	Visual studio Code
V and V	Verification and Validation

1 INTRODUCTION

In today's digital era, where information spreads at lightning speed, ensuring the credibility of news has become a critical challenge. The Fake News Detection System, powered by Machine Learning and cross-verification from internet, stands at the forefront of this issue by offering an intelligent, real-time solution for identifying and classifying misinformation. Leveraging the strengths of ML , Natural Language Processing and Internet cross-verification, this project introduces a user-friendly and effective approach to news verification in a media-driven world[1]. The rising prevalence of misinformation, particularly on social media and online platforms, calls for automated tools capable of detecting false content with accuracy and speed. The Fake News Detection System not only analyzes the textual content of news articles but also interprets and classifies them as real or fake based on learned patterns. It also helps in minimizing the spread of misleading narratives, which can influence public perception and decision-making across various sectors such as politics, health, and finance. The need for such a tool is more urgent than ever, as misinformation can escalate panic during crises, affect election outcomes, and promote harmful medical advice. Through an interactive web-based interface, users can input news text, which is instantly processed, evaluated using pre-trained ML models and cross-verified using internet. The system is designed to be fast, responsive, and user-friendly, making it ideal for both casual users and professionals[2]. By utilizing techniques like TF-IDF vectorization and Logistic Regression, this system transforms raw news content into structured data that machines can learn from and evaluate. The intelligent design ensures reliable performance while remaining simple and accessible to end-users. With clean architecture and modular development practices, this project represents a scalable solution that can adapt to evolving misinformation tactics and domains. Additionally, the model's backend structure allows for easy updates and improvements, ensuring long-term usability and relevance in combating digital misinformation. This project not only enhances digital literacy but also encourages critical thinking by providing instant feedback on the reliability of news. By integrating modern machine learning strategies with real-world application, the Fake News Detection System serves as both a technological solution and an educational tool in the fight against false information online.

1.1 Background

In recent years, the explosion of digital media and online platforms has drastically changed the way people access and share information. The Fake News Detection using Machine Learning project was initiated in response to the increasing spread of misinformation across digital platforms. In today's fast-paced information age, fake news can influence public opinion, create panic, and mislead people on a massive scale. With the widespread use of social media and online news platforms, false information can be shared within seconds, often reaching large audiences before it can be verified. This has raised serious concerns about digital trust, public safety, and the quality of information consumed daily. Traditional methods of fake news detection typically involve human verification or the use of rule-based systems. While these methods can be effective to some extent, they struggle to keep up with the volume and evolving nature of online content. They are not scalable and often fail to detect more sophisticated forms of misinformation that mimic legitimate news writing styles. These limitations created a strong need for more intelligent, automated, and adaptive systems. To address this challenge, more dynamic and automated solution using machine learning techniques is used.The system analyzes the textual content of news articles, detects linguistic patterns, and classifies the information as real or fake. It leverages the power of Natural Language Processing to understand the structure and semantics of the text. Unlike basic keyword-based tools, the model learns from large datasets and refines its predictions over time, becoming more accurate as it is exposed to more examples. Prior studies have demonstrated the potential of ML in detecting fake news. These studies inspired and informed this approach, especially in terms of dataset selection, model training, and evaluation metrics. The goal with this project is to contribute to the growing body of work in this field by offering a practical solution that can be easily deployed as a web application. This not only makes it accessible to everyday users but also demonstrates how ML can be applied to real-world problems in media literacy and online safety. By providing an interactive, efficient, and accurate platform for news verification, the project aims to empower users to make informed decisions and reduce the harmful impact of fake news on society.

1.2 Motivation

The motivation behind the Fake News Detection project arises from the increasing prevalence of misinformation in the digital age. With the rapid spread of false information across social media platforms and news websites, there is a critical need for tools that help users identify reliable sources and distinguish truth from fiction. The rise of fake news not only misguides the public but also undermines trust in legitimate news outlets. In recent years, misinformation has played a major role in influencing public opinion, spreading conspiracy theories, and creating confusion during critical events such as elections, health crises like the COVID-19 pandemic, and natural disasters. Fake news can cause panic, hatred, and even violence, making it a significant threat to societal harmony and informed decision-making. Traditional methods of verifying news manually are time-consuming and not scalable in the face of the overwhelming volume of online content. Hence, there is a growing demand for automated systems that can detect misleading or false content in real-time. Leveraging machine learning and natural language processing techniques makes it possible to build intelligent models that analyze news content efficiently and with considerable accuracy.

Figure 1.1: Motivation

1.3 Problem Statement

1. How can a fake news detection model move beyond static, outdated datasets to dynamically verify claims using real-time web sources, ensuring accuracy even for newly emerging news?

2. What techniques can be applied to detect fake news when textual data is limited, noisy, or ambiguous, especially in cases where full articles are not available-only headlines or short descriptions?

3. How many ways can input validation and classification mechanisms be refined to prevent irrelevant or non-news content (such as symbols, phrases, or names) from being processed as actual news data?

4. How can ensemble or hybrid learning approaches improve prediction accuracy and reliability across varied topics like politics, health, or entertainment, particularly in multilingual or domain-specific contexts?

5. What extent can sentiment analysis, entity recognition, and contextual embeddings be leveraged together to better differentiate fake from real news beyond keyword matching?

6. How can external fact-checking sources and multiple search engines be effectively integrated with machine learning to cross-verify claims and reduce false positives?

7. What role can web scraping from trusted news and encyclopedic sites play in supplementing model-based decisions, especially in the absence of prior data about a claim?

8. How can the system deliver intelligent handling of edge cases such as cold-starts, ambiguous inputs, and diverse formats (title-only, description-only, mixed), while maintaining user experience and accuracy?

1.4 Objectives

- To develop a fake news detection system that verifies news through two approaches: using a trained machine learning model and by cross-checking with trusted internet sources.
- To build a user-friendly web application that can identify and reject invalid inputs such as random text, symbols, or unrelated phrases, ensuring only meaningful news is processed.
- To design the system to flexibly handle and analyze multiple forms of input-news title, description, and full article-ensuring accurate verification regardless of the input structure.

1.5 Scope of Project

1.5.1 Capabilities

This project offers a comprehensive fake news detection system that combines machine learning classification with real-time cross-referencing of news content against trusted internet sources. It is specifically designed for English-language Nepali news, leveraging a carefully curated dataset that captures regional nuances and common topics. The system effectively preprocesses input text, removing noise and irrelevant content, which improves prediction accuracy. Its input validation component filters out meaningless or unrelated texts, preventing erroneous classifications. The project also features a simple, intuitive web interface developed with Flask, making it accessible to users without technical expertise. By integrating multiple verification layers, the system provides more reliable and context-aware detection of fake news, supporting efforts to reduce misinformation in Nepal's digital landscape.Overall, this system provides a balanced approach by combining machine learning with real-time verification, improving detection accuracy and usability.

1.5.2 Limitations

Despite its robust design, the system has several limitations that affect its overall performance. It cannot process news in audio or video formats and only supports news written in English. Additionally, its predictions are not always accurate, especially in ambiguous cases. The accuracy of the machine learning model is strongly dependent on the size, quality, and diversity of the training dataset, which may not capture every possible style or emerging trend in news writing. The online verification process requires access to credible and up-to-date internet sources; if such information is limited or unavailable, the system's reliability can decrease. Furthermore, the model struggles with complex content such as satire, opinion pieces, and subtle misinformation that is harder to detect. Lastly, the current implementation focuses solely on English-language Nepali news, limiting its effectiveness across other languages and geographical regions. Future improvements could include expanding the dataset, incorporating multilingual support, and refining detection of subtle misinformation like satire.

1.5.3 Feasibility Study

1. Technical Feasibility:

The Fake News Detection System is technically feasible as it utilizes widely adopted and reliable tools such as Python, Flask, Pandas and Scikit-learn. These technologies are not only open-source but also well-supported by large communities, making development and debugging easier. The system has been built and tested on a standard laptop with 8 GB RAM and an i5 processor, proving that it can run efficiently without needing high-end hardware. Its modular design also allows future improvements like multilingual support or external API integration with minimal rework.

2. Economic Feasibility:

The project is economically feasible as it has been developed using only free and open-source tools, such as Python, Flask, Pandas and Scikit-learn. There are no licensing fees, subscription costs, or paid services involved at any stage. The dataset used for training was either manually collected or obtained from publicly available sources, eliminating the need for paid data acquisition. All development, training, testing, and deployment tasks were performed locally on a personal computer, which keeps the cost of development minimal.

3. Operational Feasibility:

The system is highly feasible and user-friendly. It features a clean web interface built with HTML, CSS, and Flask, allowing users to input news in the form of a title, description, or full article. Real-time results, customizable verification options, and strong input validation make it accessible to a wide range of users, even those without technical expertise. The system requires no complex infrastructure, databases, or continuous maintenance, which makes it easy to manage and deploy in practical settings.

4. Schedule Feasibility:

The development of the Fake News Detection System was completed within the allocated timeframe, following a planned schedule. All major phases—such as data collection, model training, system design, and web integration—were carried out in a timely manner. This confirms that the project was manageable within the given project timeline, ensuring its feasibility from a scheduling perspective.

1.6 Potential Project Applications

1. Social Media Platforms: The fake news detection system can be integrated into social media platforms to automatically identify and flag misleading news articles or posts. This would help users quickly discern credible information from misleading or false narratives, contributing to a more reliable online environment.

2. News Websites: News organizations and websites can utilize this tool to verify the authenticity of articles before publication. By running news content through the fake news detection system, websites can ensure that they only release verified and factual information, reducing the spread of misinformation.

3. Fact-Checking Agencies: Fact-checking organizations can benefit from the tool as an automated assistant to quickly analyze large volumes of news content. The system can help these agencies identify suspect articles and prioritize those for further investigation, speeding up the fact-checking process.

4. Improving Public Awareness and Safety: Fake news detection systems help prevent the spread of misinformation during critical events such as elections, pandemics, or natural disasters. By identifying and flagging false content early, these systems protect the public from making decisions based on lies or half-truths, thereby promoting informed choices and reducing panic or confusion.

6. Government and Law Enforcement Agencies: Government departments and law enforcement agencies can leverage the fake news detection system to identify and monitor the spread of harmful misinformation across digital platforms. During elections, national crises, or public health emergencies, false narratives can rapidly escalate tensions or lead to mass confusion. By using this system, authorities can detect misleading content early, take corrective action, and issue official clarifications to counteract falsehoods. Additionally, it aids in cybercrime investigations by tracing sources of fake news, preventing the deliberate spread of propaganda, hate speech, or incitement to violence.

7. News Agencies: News agencies can use the fake news detection system to verify the authenticity of articles before publication. By integrating the tool into their editorial workflow, agencies can automatically scan content for potential misinformation and flag suspicious pieces for manual review. This helps maintain journalistic integrity, reduces the risk of spreading false information, and protects the agency's reputation. It also ensures that only fact-checked and credible news reaches the public, enhancing audience trust and media accountability.

8. Controlling Rumors and Misinformation: The fake news detection system can be effectively used by organizations and public authorities to identify and curb the spread of rumors and misinformation, especially during crises such as pandemics, natural disasters, or social unrest. By quickly detecting false or misleading content circulating on social media and messaging platforms, the system enables timely intervention to prevent panic, confusion, and harmful consequences. It supports efforts to provide accurate information, restore public trust, and maintain social stability during critical situations.

1.7 Originality of Project

This project introduces a fake news detection system that analyzes news text using dual approach: **it classifies the input through a machine learning model trained on a custom dataset and simultaneously verifies the content in real-time by cross-checking trusted online sources.** Unlike many systems that rely only on static models or external APIs, this combined method enhances accuracy and reliability by leveraging both historical data and live information. The project includes a standalone Flask-based web application where users can input news content and receive instant feedback from both detection layers. This integration of machine learning with real-time online verification, paired with a user-friendly interface, makes the system practical and accessible for educators, fact-checkers, and everyday users seeking trustworthy news validation.These following factors make the project unique among others.

1. **Dual-Layer Verification:**
   The system uniquely integrates both machine learning and web-based verification methods, allowing more accurate and trustworthy classification compared to systems that rely on only one approach.

2. **Flexible Input Handling:**
   It accepts news in the form of title, description, or full article—ensuring flexibility and adaptability to real-world use where users might have only partial information.

3. **Input Validation Layer:**
   The system includes a smart input filter that rejects non-news content such as random characters, numbers, or unrelated sentences, ensuring meaningful analysis and improving model reliability.

4. **User-Selectable Verification Mode:**
   Users are given control over how the news is verified-whether to use only ML, only web verification, or both-making the system more interactive and user-driven.

5. **Custom Dataset Curation:**
   The machine learning model is trained on a manually collected dataset specific to the project, enhancing domain relevance and reducing dependence on generic or outdated datasets.

6. **Modular and Offline-Capable Design:**
   The system can run fully on local machines without internet dependency for ML-only mode, making it suitable for academic or restricted environments.

1.8 Organization of Project

The material in this project report is organized into six chapters. After the introductory chapter in Chapter 1,it introduces the problem topic and addresses it. Chapter 2 contains the literature review of vital and relevant publications, pointing toward notable research gap. Chapter 3 describes the methodology for the implementation in the project. Chapter 4 provides an overview of the project as results.Chapter 5 provides an overview of the project as discussion and analysis.Chapter 6 provides the future enhancement of the project.

2 LITERATURE REVIEW

2.1 Literature Review I

Fake news, which involves false or misleading information, can significantly influence public opinions, political views, and social stability. Detecting and addressing fake news has become crucial, and machine learning offers a promising solution. Recently, various ML techniques, particularly those in natural language processing , have been employed to automatically classify news articles as either real or fake. Supervised learning is a widely used approach in fake news detection. This method involves training models on labeled datasets containing both real and fake articles. Algorithms like Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machines are commonly used, relying on features such as term frequency-inverse document frequency and bag-of-words[1] .Additionally, deep learning techniques, including Recurrent Neural Networks and Long Short-Term Memory networks, capture the sequential nature of text and improve the identification of subtle patterns. Studies, show that these models can effectively detect fake news when properly applied. Unsupervised learning methods have also been explored, which don't require labeled data. Clustering techniques, like k-means, group similar articles, helping to spot fake news by identifying patterns in writing styles and content[1]. While unsupervised methods can uncover hidden patterns, they tend to be less precise due to the lack of explicit labels. To improve accuracy, hybrid models combining supervised and unsupervised learning have been proposed. These models integrate text features with additional data, such as social media metadata, to enhance detection by providing more context. However, several challenges remain in fake news detection. One major issue is data imbalance, where fake news datasets often contain more real news than fake articles, leading to a bias toward classifying articles as real. Techniques like oversampling, undersampling, and synthetic data generation have been used to address this imbalance. Another challenge is contextual understanding. Fake news often uses emotional language or sensational headlines, making it harder for models to detect. Advanced models like Bidirectional Encoder Representations from Transformers have shown promise in capturing deeper contextual meaning, helping address this issue.

2.2 Literature Review II

In today's digital world, the spread of fake news has become a serious concern, especially with the rise of social media and online platforms. Fake news can mislead people, shape public opinion in harmful ways, and even disrupt political processes. Because of this, the need to detect and stop fake news has become more urgent than ever, and machine learning has emerged as a powerful tool to tackle this problem[3]. This literature review dives into the various machine learning methods that have been explored for fake news detection, focusing on supervised learning, unsupervised learning, and hybrid approaches. Supervised learning is one of the most commonly used techniques for detecting fake news. In this approach, models are trained using datasets that are already labeled with either real or fake news[3]. A variety of machine learning algorithms, including Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machines , have been widely used in this space. These models often rely on features such as (term frequency-inverse document frequency) and bag-of-words to convert text into numerical form that the model can process. While these methods are effective, they come with one major challenge: they require large amounts of labeled data, which can sometimes be difficult or costly to obtain. On the other hand, unsupervised learning techniques don't require labeled data and can help uncover patterns without needing explicit categorization. Clustering algorithms like k-means and techniques like topic modeling have been explored for this task. These methods group articles based on similarities in content and writing style, which can help identify fake news by spotting unusual or suspicious patterns. However, unsupervised methods aren't as precise as supervised ones because they lack clear labels to guide the learning process, making it harder to distinguish between fake and real news effectively. In recent years, deep learning techniques have also made a huge impact on fake news detection. Models like Recurrent Neural Networks and Long Short-Term Memory networks are great at processing sequential data, such as text, because they can capture the relationships between words across sentences and paragraphs. This ability allows them to pick up on subtle cues and patterns in language that might indicate fake news. Moreover, transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) have further pushed the boundaries of what's possible.

2.3 Literature Review III

In the current digital landscape, the rapid dissemination of fake news has emerged as a major societal challenge. With the increasing reliance on online news sources and social media platforms, misinformation can spread quickly, influencing public sentiment and distorting reality. Addressing this issue requires reliable detection techniques, and machine learning has proven to be one of the most promising solutions in this field[2]. This review highlights various ML strategies for fake news detection, focusing on supervised, unsupervised, and deep learning approaches. Supervised learning remains the most widely adopted technique for detecting fake news. In this approach, models are trained using datasets labeled as ”fake” or ”real.” Commonly used classifiers include Decision Trees, Naive Bayes, Support Vector Machines , and Logistic Regression. These models typically use feature extraction techniques like TF-IDF or CountVectorizer to convert raw news text into a format suitable for learning[2]. Although these models are often effective, they heavily depend on the availability of large, well-annotated datasets, which can be both time-consuming and resource-intensive to develop. In contrast, unsupervised learning techniques bypass the need for labeled data. Instead, they identify hidden structures or similarities within unlabeled text. Algorithms such as k-means clustering or Latent Dirichlet Allocation for topic modeling have been employed to group news articles by writing patterns or thematic similarities. While useful for discovering trends, these methods are generally less accurate than supervised models due to the absence of ground-truth labels. More recently, deep learning techniques have revolutionized fake news detection by leveraging the contextual and sequential nature of text. Models like Convolutional Neural Networks , Recurrent Neural Networks , and Long Short-Term Memory networks are capable of recognizing intricate linguistic patterns and dependencies. Furthermore, transformer-based models such as BERT have advanced the field by offering a deeper understanding of context through bidirectional learning. These models not only improve detection accuracy but also reduce the need for extensive manual feature engineering. Overall, while each method has its strengths and limitations, the integration of traditional ML with deep learning and natural language processing continues to enhance the effectiveness of fake news detection systems.

2.4 Literature Review IV

In recent years, the detection of fake news has become a critical area of research due to the widespread influence of misinformation across social media and online platforms. In their paper, "A Comparative Study of Machine Learning and Deep Learning Techniques for Fake News Detection", present an extensive benchmark analysis that evaluates and compares a broad range of machine learning and deep learning models to address this pressing challenge[4]. The study is notable for its comprehensive coverage of models. It examines classical ML algorithms, including Logistic Regression , Support Vector Machines , Decision Trees , Naive Bayes, Random Forest , and XGBoost . These models are well-established in text classification and continue to serve as strong baselines for fake news detection due to their simplicity and effectiveness on structured datasets[4]. However, Author highlight the limitations of these models in capturing contextual and semantic nuances in textual data. To overcome these limitations, the authors also explore advanced deep learning models, such as Convolutional Neural Networks , Bidirectional Long Short-Term Memory , Bidirectional Gated Recurrent Units , and hybrid models like CNN-BiLSTM and CNN-BiGRU. These models are designed to understand sequential dependencies and contextual relationships in language, making them better suited for detecting complex patterns in news articles. Furthermore, the paper emphasizes the effectiveness of transformer-based models like BERTbase and RoBERTabase, which are capable of capturing deep contextual embeddings of text. The authors compare traditional context-independent embeddings like GloVe with BERT's contextualized representations and report significantly improved performance. Experiments were conducted on four widely used real-world datasets—LIAR, PolitiFact, GossipCop, and COVID-19—demonstrating that deep learning and transformer models consistently outperform classical ML approaches when sufficient data is available. Notably, the results were achieved by relying solely on the textual content of news articles, without incorporating social context or metadata. This study provides valuable insights into the comparative performance of ML and DL techniques in fake news detection and highlights the growing importance of deep contextual understanding in combating misinformation online.

2.5 Literature Review V

The rapid spread of fake news has posed significant challenges to the reliability of information disseminated through digital media platforms. To tackle this issue, researchers have increasingly turned to deep learning techniques, which offer enhanced capabilities over traditional machine learning algorithms in detecting deceptive content. Conventional methods such as Logistic Regression, Support Vector Machines , Naïve Bayes, and Random Forest rely heavily on manually engineered features and often struggle to capture the nuanced linguistic patterns that characterize fake news [5]. In contrast, deep neural networks excel at automatically learning complex representations from raw textual data, enabling improved classification accuracy and robustness. Author conducted a comprehensive study investigating various deep learning architectures applied to fake news detection, demonstrating that deep neural networks consistently outperform classical classifiers [5]. Their research highlights how integrating deep learning with established feature extraction techniques, such as TF-IDF and word embeddings, can further enhance model performance. The authors experimented with multiple configurations and reported notable improvements in precision and recall, underscoring the effectiveness of these models in distinguishing between genuine and fabricated news articles. Despite the promising results, deep learning approaches face several limitations that must be addressed for practical deployment. One of the primary challenges is the need for large, well-labeled datasets, which are often scarce or difficult to curate due to the dynamic nature of fake news content. This scarcity hampers the ability of deep models to generalize effectively across diverse news domains and topics. Additionally, deep neural networks are commonly regarded as "black boxes," providing limited interpretability regarding their decision-making processes. This opacity poses ethical and trust concerns, as end-users and stakeholders may require explanations to validate the model's outputs before relying on them for critical decisions. Furthermore, the computational complexity of training and deploying deep learning models can be a barrier, especially for real-time applications where timely detection is essential. In summary, deep learning techniques represent a significant advancement in the field of fake news detection, offering superior accuracy and adaptability compared to traditional methods. However, ongoing research must focus on overcoming challenges related to data availability, model interpretability, and computational efficiency.

2.6 Literature Review VI

The proliferation of fake news across social media and digital platforms has posed significant challenges for information verification, driving the need for advanced detection mechanisms. Recent developments in deep learning, especially Convolutional Neural Networks , have demonstrated notable improvements in automatically identifying fake news by effectively capturing complex textual patterns that traditional machine learning models often fail to recognize. Author introduced OPCNN-FAKE, an optimized CNN architecture specifically tailored for fake news detection, which incorporates multiple convolutional layers designed to extract hierarchical features from textual data [6]. The model integrates advanced training techniques such as dropout and batch normalization, which enhance the model's ability to generalize and reduce overfitting, particularly when handling noisy and unstructured data commonly encountered in online news articles. Their extensive experiments revealed that OPCNN-FAKE outperforms classical classifiers including Support Vector Machines , Naïve Bayes, and basic CNN models, achieving higher precision, recall, and overall accuracy. Moreover, Saleh et al. emphasize that the success of OPCNN-FAKE lies in adapting CNN architectures—originally designed for image processing—to the unique challenges of natural language, such as capturing semantic and syntactic nuances within fake news content [6]. The optimized convolutional filters in their approach are able to discern subtle linguistic cues and contextual relationships that distinguish misleading news from authentic reporting. Despite these promising results, the study acknowledges persistent challenges, such as the dependence on large, well-annotated datasets required for training deep models effectively, which can be difficult to obtain given the evolving nature of fake news narratives. The computational demands of deep learning models like OPCNN-FAKE also pose barriers for real-time deployment in resource-constrained environments, necessitating further research into model compression and efficient inference techniques. Nevertheless.. Their approach lays a foundation for future exploration of hybrid models that combine CNNs with other modalities, such as user behavior data or metadata, to further improve detection accuracy. Overall, this study exemplifies how tailored deep learning frameworks, when properly tuned and trained, can effectively address the challenges posed by misinformation, offering a powerful tool to enhance the credibility and reliability of information circulated on digital platforms.

2.7 Literature Review VII

The challenge of detecting fake news in the era of widespread misinformation has led to significant research efforts focusing on deep learning techniques due to their superior ability to learn complex patterns in large datasets. Author provided a comprehensive review of fake news detection methods using deep learning, highlighting the importance of models such as Convolutional Neural Networks , Recurrent Neural Networks , and hybrid architectures in improving detection accuracy [7]. Their study underscores how deep learning models surpass traditional machine learning algorithms by automatically extracting relevant features without the need for extensive manual preprocessing. Furthermore, the authors emphasize that combining multiple neural network architectures can enhance performance by leveraging complementary strengths, such as integrating feature extraction with RNNs' contextual understanding.The Study also discuss various challenges inherent in fake news detection, including the scarcity of large annotated datasets, the dynamic and evolving nature of misinformation, and the need for models that are both accurate and interpretable [7]. They point out that deep learning models often require vast computational resources and may suffer from issues related to overfitting, which can degrade their generalization to unseen data. To address these problems, recent studies have explored transfer learning and attention mechanisms, which help models focus on critical parts of the text and adapt to new contexts with limited data. The review highlights the role of natural language processing techniques combined with deep learning to better understand the semantics and pragmatics of news content, allowing for more nuanced differentiation between real and fake news.it notes the growing trend of incorporating multimodal data, such as images and social network metadata, to provide richer contextual information that improves detection capabilities. the work provides a valuable synthesis of current deep learning approaches to fake news detection, illustrating how advancements in neural networks have contributed to more robust and scalable solutions. Their findings suggest that while deep learning holds great promise, continued efforts are necessary to overcome challenges related to data availability, interpretability, and computational efficiency. This comprehensive review serves as a crucial resource for researchers aiming to develop more effective fake news detection systems that can keep pace with the rapidly changing landscape of misinformation.

2.8 Literature Review VIII

The challenge of detecting fake news has attracted significant attention due to the serious consequences that misinformation can have on public opinion, political stability, and social trust. Their study begins with an emphasis on the importance of preprocessing textual data, which includes steps such as removing noise like punctuation and stopwords, converting text to lowercase to maintain uniformity, and applying tokenization to break text into meaningful units[8]. After preprocessing, feature extraction plays a crucial role, with the use of term frequency-inverse document frequency and n-gram models to numerically represent the text. These features capture both the importance of words and their context, which are essential for distinguishing between genuine and fake news. it evaluated multiple traditional machine learning classifiers including Logistic Regression, Support Vector Machines , and Random Forest. Their experiments demonstrated that with well-engineered features and balanced datasets, these models can achieve reliable classification performance, despite the challenges posed by imbalanced data where real news articles outnumber fake ones, a common scenario in this domain. To overcome this, they applied sampling techniques that helped balance the datasets, which improved the sensitivity of their models to fake news detection[8].One such challenge is the constantly evolving nature of misinformation, which often changes its language style and strategies to evade detection. This dynamic nature requires models to be regularly updated with fresh data to maintain their accuracy and effectiveness. The study contrasts traditional machine learning techniques with emerging deep learning methods, pointing out that while deep learning models such as neural networks have the ability to learn complex patterns automatically, traditional methods still hold advantages in terms of interpretability and computational efficiency. These factors make classical machine learning approaches more suitable in scenarios with limited computational resources or where model transparency is essential for trust and accountability. Integrating this additional metadata with textual analysis could create more comprehensive detection systems that not only analyze the content but also understand how misinformation spreads across networks. Their findings provide a solid foundation for future research and practical implementations aimed at building robust, scalable, and adaptable fake news detection systems that combine the strengths of both machine learning and natural language processing to tackle the ever-changing landscape of misinformation.

2.9 Summary of Literature Review

Author/Year	Focus	Methodology	Key Findings	Contributions
Lit. Review I, 2025	ML methods for fake news detection	Sup: LR, NB, RF, SVM; Unsup: k-means; Hybrid; Features: TF-IDF, BERT	Sup effective but needs labeled data; hybrid improves context; challenges: imbalance, contextuality	Overview of ML techniques; highlighted data imbalance and context issues
Lit. Review II, 2025	ML and DL for fake news	Sup, Unsup, DL (RNN, LSTM, BERT)	DL captures sequential/contextual cues better; unsupervised less precise; labeled data needed	Showed importance of DL and transformers for better accuracy
Lit. Review III, 2025	ML and DL approaches	Sup: DT, NB, SVM, LR; Unsup: k-means, LDA; DL: CNN, RNN, BERT	DL reduces manual feature engineering; transformers improve detection	Illustrated shift from classical ML to DL techniques
Patwa et al., 2021	COVID-19 fake news dataset	Multimodal dataset from social media and news with metadata	Enables benchmarking; supports multimodal and temporal analysis; publicly available	Provided important COVID-19 misinformation dataset
Khanam et al., 2021	ML classifiers for fake news	LR, SVM, RF; TF-IDF, n-grams; evaluated with multiple metrics	LR highest accuracy; RF robust; ensemble and oversampling improve results	Validated classical ML approaches; suggested ensemble methods
Li et al., 2021	Survey of ML methods	Supervised, Unsupervised; feature engineering; multi-modal data	Challenges include evolving fake news and dataset bias; stressed real-time and explainability	Comprehensive review guiding future research directions
Dixit et al., 2022	ML algorithms and feature engineering	LR, SVM, RF, GB; preprocessing: stemming, lemmatization; TF-IDF	Ensemble classifiers improved accuracy; balanced data reduces bias; dataset size limited	Highlighted preprocessing importance; recommended DL for future work
Rashid et al., 2023	Feature extraction and model evaluation	Enhanced TF-IDF; LR on balanced data; dimensionality reduction	Improved accuracy and efficiency; faster training; suggested DL integration	Demonstrated benefits of advanced feature extraction and preprocessing

Table 2.1: Summary of Literature Review

3 METHODOLOGY

3.1 Theoretical Formulation

The theoretical formulation of the Fake News Detection system is based on several core concepts from Natural Language Processing , supervised machine learning, and web application development using Flask. This section outlines the key theoretical foundations applied in the system's design and implementation.

Web Development using Flask

The fake news detection system is implemented as a lightweight and interactive web application using the Flask framework. Flask is a Python-based micro web framework that supports rapid backend development. In this project, it serves as the bridge between the machine learning model and the user interface. The frontend of the application is built using static HTML, CSS, and JavaScript files. These components provide a user-friendly interface where users can input a news headline or article text. When the user submits input through the HTML form, the data is sent to the Flask backend via a defined route. On the backend, Flask processes the input, applies the same preprocessing steps used during model training, loads the trained machine learning model , and generates a prediction (real or fake).

1. **Natural Language Processing**

   NLP techniques are applied to clean and structure the text before feeding it to the machine learning model. The preprocessing pipeline involves several sequential operations:

   - **Tokenization:** Splitting the news text into individual words or tokens.
   - **Stopword Removal:** Eliminating common words (e.g., ”is”, ”and”) that do not contribute to meaning.
   - **Lowercasing:** Converting all characters to lowercase for uniformity.
   - **Punctuation Removal:** Cleaning punctuation marks that have no semantic value.
   - **Lemmatization:** Reducing words to their root form (e.g., ”running” becomes ”run”).

These steps reduce noise in the dataset and ensure that the text is standardized before being transformed into numerical form.

2. **Feature Extraction using TF-IDF**

   After preprocessing, the clean text is converted into numerical vectors using the Term Frequency-Inverse Document Frequency technique. TF-IDF assigns weights to each word based on:

   - **Term Frequency :** How often a word appears in a document.
   - **Inverse Document Frequency :** How unique or rare the word is across all documents.

   This representation emphasizes unique and informative words, which helps the model differentiate between real and fake content.

3. **Major Benefits of the Chosen Techniques**

   Each technique used in this system offers distinct advantages that contribute to the effectiveness, efficiency, and reliability of the fake news detection process.

   - **Flask for Web Development:** Flask is lightweight, easy to use, and ideal for developing quick prototypes and scalable applications. It allows seamless integration with Python-based machine learning libraries and provides flexibility in routing and backend logic. This results in a responsive web interface that can efficiently communicate with the ML model.
   - **Natural Language Processing:** NLP enables the system to understand and process unstructured human language. The applied techniques-tokenization, stopword removal, lowercasing, punctuation removal, and lemmatization-significantly improve model performance by reducing noise and focusing on semantically meaningful content. This enhances the system's ability to generalize across different types of news articles.
   - **TF-IDF for Feature Extraction:** TF-IDF is effective in highlighting important words while downplaying frequently occurring but less informative terms. This sparse and weighted representation allows the machine learning

model to focus on keywords that are more indicative of the article's authenticity. Moreover, it helps reduce dimensionality and overfitting, especially when dealing with limited datasets.

- **Supervised Machine Learning Model:** The use of supervised learning (such as Logistic Regression) provides a transparent and interpretable decision boundary, which is valuable for binary classification tasks like fake vs real news. It also enables quick retraining and model updates as new data becomes available.

4. **Assumptions Considered**

The development of the fake news detection system is based on several practical and theoretical assumptions that help simplify the problem space and guide the implementation process. These assumptions are made to maintain consistency, enhance model reliability, and ensure smooth integration between components.

- **Input Text Represents News Content:** It is assumed that users will input text that resembles genuine news headlines or descriptions. The system is not designed to process unrelated content such as random phrases, numerical entries, or informal chat language.
- **Text is in English Language:** The entire pipeline-including preprocessing, feature extraction, and model training—assumes that all news content is written in English. Non-English input is not supported in the current system version.
- **Trained Model is Generalizable:** The machine learning model is assumed to perform reliably on unseen news samples from similar sources and formats as those present in the training dataset. It is expected to generalize well within the boundaries of typical news content.
- **User-Submitted Text is Pre-verified:** It is assumed that the input text has not been manipulated in a way that misleads the classifier (e.g., mixing fake and real content in one sentence). The system relies on clearly stated input for binary classification.

3.2 Mathematical Modelling

The mathematical modelling for this fake news detection system is based on key techniques from Natural Language Processing and supervised Machine Learning . It outlines how raw news text is processed, represented numerically, and used for classification.

3.2.1 Text Representation using TF-IDF

To begin, raw text from news articles is transformed into numerical vectors using Term Frequency–Inverse Document Frequency . This method evaluates how important a word is to a document in a collection.

Term Frequency :

$$TF(t) = \frac{\text{Number of times term } t \text{ appears in a document}}{\text{Total number of terms in the document}} \tag{3.1}$$

Inverse Document Frequency :

$$IDF(t) = \log\left(\frac{N}{n_t}\right) \tag{3.2}$$

Where: N = Total number of documents in the corpus n_t = Number of documents where term t occurs

TF-IDF Score:

$$TF\text{-}IDF(t) = TF(t) \times IDF(t) \tag{3.3}$$

This score gives higher weight to words that are frequent in one document but rare across others, making them more useful for classification.

3.2.2 Classification with Logistic Regression

Once each news article or title is represented as a vector, the next step is classification. Logistic Regression is applied to determine the likelihood of the article being fake or real based on the feature values.

Sigmoid Function:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{3.4}$$

Where:

$$z = w_1x_1 + w_2x_2 + \cdots + w_nx_n + b \tag{3.5}$$

Here: x_i = TF-IDF score for word i w_i = model weight for feature i b = bias term

Prediction Rule:

$$\sigma(z) \geq 0.5 \Rightarrow \text{Real News}, \qquad \sigma(z) < 0.5 \Rightarrow \text{Fake News}$$

The sigmoid function converts the weighted sum into a probability between 0 and 1, which is then used for binary classification.

3.2.3 Training with Binary Cross Entropy

To train the model effectively, the Binary Cross Entropy loss function is used. It calculates the difference between predicted probabilities and actual labels.

$$L = -\left[y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})\right] \tag{3.6}$$

Where: y = actual class label (1 for real, 0 for fake) $\hat{y}$ = predicted probability from the sigmoid output

This function penalizes wrong predictions and helps guide the model during training to improve accuracy.

3.2.4 Evaluation Metrics

After training, the model's performance is measured using the following metrics:

Accuracy:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{3.7}$$

Precision:

$$Precision = \frac{\text{True Positives}}{\text{True Positives + False Positives}} \tag{3.8}$$

Recall:

$$Recall = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \tag{3.9}$$

F1 Score:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{3.10}$$

These metrics give a balanced overview of the model's ability to correctly classify both real and fake news, especially in cases of imbalanced data.

3.3 System Block Diagram

This block diagram illustrates the flow of data and processing in Fake News Detection system.

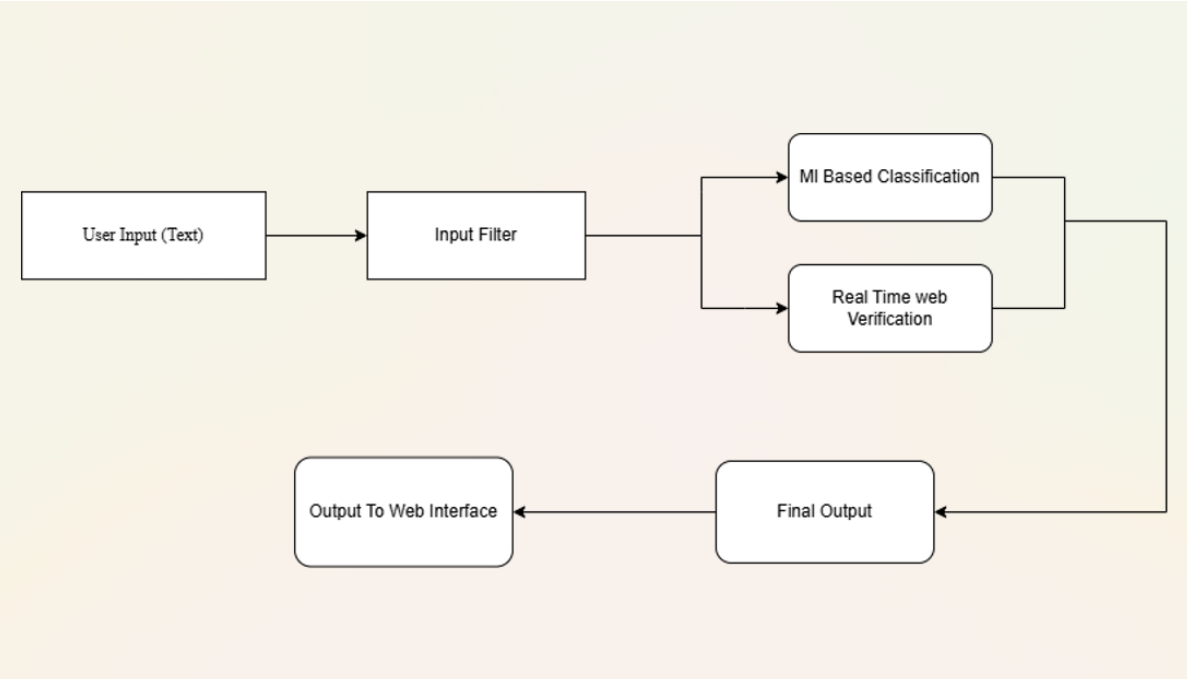

Figure 3.1: System Block Diagram

- **User Input (Text):** This is the initial block of the system where the user provides input in the form of a news headline or full news description. The system accepts text-only input and ensures that the entered content is complete and relevant for processing.

- **Input Filter :** The input validator module performs a preliminary check on the submitted text. It removes or rejects inputs that are too short (e.g., less than three words), contain only symbols or numbers, or do not resemble real news content (e.g., ”I love you”, ”What’s your name”). This ensures that only meaningful content proceeds to the next stage.

- **ML Based Classification :** This block represents the machine learning-based component of the system. The cleaned text is first transformed into numerical features using the TF-IDF technique. These features are then fed into a trained Logistic Regression model, which predicts whether the news is real or fake based on patterns learned during training on the custom dataset.

- **Real Time Web Verification :** Simultaneously, the system checks the input text against credible and trusted online sources (such as news websites or fact-checking databases). If a similar or identical article is found, the system uses that result to further support or contradict the machine learning classification. This adds an extra layer of reliability through real-time online verification.
- **Final Output:** This block combines the outputs of both the ML classifier and the online verification system. It compares the results and makes a final decision based on their agreement or disagreement. If both modules indicate the news is real, the final result is marked as real; if there's conflict or both mark it fake, the result is flagged accordingly.
- **Output to Web Interface:** The final block presents the result to the user via a simple web interface. It shows whether the news is classified as real or fake and optionally provides additional suggestions, warnings, or confidence scores. The interface is built using Flask, making it accessible and responsive.

3.4 Instrumentation Requirements

Requirements	**Details**
Software Requirements	• Operating System: Windows 10 or 11 • Browser: Any (Chrome/Edge preferred) • Code Editor: Visual Studio Code
Hardware Requirements	• RAM: Minimum 4 GB • Internet Speed: Minimum 10 Mbps • Storage: 128 GB SSD or more • Processor: Intel i5 or equivalent, at least 2.4 GHz
Language Used	• Python • HTML • CSS • JavaScript
Libraries/Frameworks Required	• Scikit-learn • Pandas • Numpy • Flask • HTML/CSS/JavaScript (for frontend)

Table 3.1: Instrumentation Requirements

The development and deployment of the Fake News Detection system were carried out on a personal computing device that offered reliable hardware capabilities suitable for both machine learning tasks and web application integration. The laptop used during the entire project lifecycle was configured with 8 GB of RAM, a 556 GB Solid State Drive , and an 11th Generation Intel processor, running on the Windows 11 operating system. This configuration provided a stable and responsive environment, allowing for smooth execution of preprocessing scripts, model training routines, and Flask-based web server hosting.

For software development, Visual Studio Code was the primary integrated development environment used to write and organize the Python scripts, manage virtual environments, and debug the application. Python served as the core programming language due to its rich ecosystem of libraries such as Scikit-learn, Pandas, NumPy, and Flask, all of which played crucial roles in implementing machine learning models, handling data operations, and creating the web interface. Additionally, for the preparation of this academic report and technical documentation, the LaTeX typesetting system was used. LaTeX offered fine control over formatting, referencing, and structuring of the content, making it ideal for producing a professional-grade final report. The combination of capable hardware and carefully chosen software tools contributed significantly to the seamless execution and completion of the project.

The primary purpose of the computing device in this project was to serve as the central platform for the complete development, testing, and execution of the fake news detection system. It was used to write and organize code, preprocess data, train and evaluate machine learning models, and deploy the web application locally using the Flask framework. The device also facilitated real-time interaction between the frontend interface and the backend logic, ensuring smooth functionality during user input and prediction generation. Additionally, it played a key role in managing library installations, handling file storage for datasets and models, and supporting the documentation process using LaTeX. In essence, the device functioned as both the development environment and testing ground for the system, enabling all stages of the project to be executed efficiently in a self-contained setup.

3.5 Dataset Explanation

The dataset used in this Fake News Detection project plays a crucial role in training and evaluating the machine learning model. It contains labeled news articles classified into two categories: real and fake. This clear distinction allows the model to learn linguistic and structural patterns typical of trustworthy versus misleading news.

The dataset was collected and prepared in two parts. Initially, a publicly available dataset was used to establish the baseline performance of the model. It contains separate CSV files for real and fake news, each including key attributes such as the news title, description, and occasionally, the source and date. These fields provide enough information for effective text-based classification using NLP techniques. To improve the contextual relevance and to simulate real-world data, we further extended the dataset manually. This involved curating a small set of recent Nepali news articles (written in English) from trusted media sources. These were manually labeled and added to the dataset to ensure broader coverage across domains like politics, entertainment, and sports. The resulting dataset is thus a combination of both publicly sourced and manually collected entries, providing a realistic and diverse set of samples for the model to learn from. It supports robust generalization, as it covers varying writing styles, vocabulary, and content tones.

label	title	description	subject	date
fake	pip install --	A leaked dc	Politics	4/15/2025
fake	Kathmandu	Insider sou	Politics	4/20/2025
fake	Nepal Elect	A whistlebl	Politics	4/25/2025
fake	Nepal’s Op	Explosive re	Politics	4/30/2025
fake	Secret Bill t	A hidden pa	Politics	5/5/2025
fake	Nepal’s Pre	Shocking ru	Politics	5/10/2025
fake	Nepal’s Arn	A whistlebl	Politics	5/15/2025
fake	Kathmandu	Leaked ema	Politics	5/20/2025
fake	Nepal’s PM	A viral vide	Politics	5/25/2025
fake	Nepal’s Par	A secret bill	Politics	5/30/2025
fake	Kathmandu	Panic sprea	Society	4/12/2025
fake	Nepali Teer	A viral TikTo	Society	4/17/2025
fake	Ghost of Ki	Tourists an	Society	4/22/2025
fake	Nepali Schc	Parents are	Society	4/27/2025

Figure 3.2: Fakenews Dataset

label	title	description	subject	date
real	Govt at woı	Prime Minis	politics	4/12/2025
real	Teachers' Fe	The Nepal T	politics	4/17/2025
real	President s	President R	politics	4/16/2025
real	Rabi Lamich	Rastriya Sw	politics	4/17/2025
real	In pictures:	Former Hor	politics	.0/19/2024
real	Maoist Cen	The Eighth (	politics	1/2/2022
real	National As	The Nationa	politics	3/30/2025
real	Opposition	Several opp	politics	4/10/2025
real	Federal Parl	The Federal	politics	5/1/2025
real	Governmen	The governi	politics	4/25/2025
real	Spiritual dis	A spiritual c	society	3/2/2024
real	Nepal clinch	Nepal's culi	society	1/15/2025
real	Community	Local comm	society	4/10/2025
real	Women ent	There has b	society	3/28/2025
real	Cultural fes	The annual	society	2/20/2025
real	Youth volur	Youth volur	society	1/30/2025

Figure 3.3: Realnews Dataset

3.6 Dataset Description

The dataset used in this project consists of structured news data categorized into several key columns. Each column carries distinct information required for training, testing, and evaluating the fake news detection model. Below is a detailed explanation of each attribute:

1. **Label**

   The label column indicates whether the news article is real or fake. In this dataset, all values are marked as real, signifying that the current portion represents authentic news content. This binary classification label is essential for supervised learning, where the model learns to distinguish between real and fake news based on labeled examples.

2. **Title**

   The title column contains the headline or title of the news article. Titles are often short, attention-grabbing phrases that summarize the core of the news. In the model pipeline, titles can be used independently or in combination with the description to form the input features for classification.

3. **Description**

   The description column provides a short summary or opening lines of the news article. This text offers more context than the title and is particularly useful for understanding the subject matter. It plays a vital role in improving the accuracy of the model by offering richer textual input.

4. **Subject**

   The subject column categorizes the article into domains such as politics or society. This field is useful for understanding the thematic distribution of the dataset and can also assist in creating domain-specific classifiers if needed. It also helps ensure that the model does not develop a bias toward a specific news category.

5. **Date**

   The date column records the publication date of the news article. The date is useful for sorting, filtering, or performing temporal analysis. Although not directly used in model training, it can be helpful in data validation, trend analysis, or for time-based splitting of training and testing sets.

3.7 Description of Algorithms

The fake news detection system follows a hybrid approach combining machine learning classification with real-time web verification. This algorithm ensures that the input news content is not only checked against a trained dataset but also validated live through online sources to enhance credibility and accuracy. The complete working mechanism is described below in sequential stages:

1. **User Input:** The system starts when a user enters a news headline or full content through the web application interface.

2. **Input Validation:** The system first checks if the input text is meaningful and sufficient. Inputs with less than three words or irrelevant content (e.g., random phrases, greetings, or symbols) are rejected and an error message is displayed.

3. **Text Preprocessing:** If valid, the input undergoes text preprocessing to prepare it for analysis. This involves:

- Converting text to lowercase
- Removing punctuation, special characters, and HTML tags
- Eliminating stopwords (e.g., ”the”, ”is”, ”in”)
- Applying lemmatization to reduce words to their base form

4. **Feature Extraction (TF-IDF):** The cleaned text is converted into a numerical format using the Term Frequency–Inverse Document Frequency (TF-IDF) method. This step transforms text into vectors that represent word importance in the context of the entire dataset.

5. **Machine Learning Classification:** The TF-IDF vectors are fed into a pre-trained Logistic Regression model. The model outputs a probability score indicating how likely the input is to be real or fake. If the score is above a defined threshold (typically 0.5), the model classifies the content as real; otherwise, it is labeled as fake.

6. **Real-Time Web Verification:** Parallel to the ML prediction, the system performs a web search on trusted news websites using the input text. It attempts to find similar headlines or descriptions across the internet. If relevant matches are found on reputable sources, the content is further validated.

7. **Decision Logic:** The final output depends on the user’s selected verification mode:
   - If no option is selected, only the machine learning model is used to classify the news as Real or Fake.
   - If the user selects Web only, the system performs a real-time web search and provides the result based solely on matches found across trusted sources.
   - If the user selects ML + Web, the system runs both methods independently and displays the results of both approaches side by side.

8. **Output Display:** Based on the selected mode, the system displays the result(s) on the web interface:
   - ML only: Single result from the machine learning model.
   - Web only: Single result from real-time web verification.

- ML + Web: Dual result showing outputs from both ML and Web side by side.

3.8 Pseudocode Representation

Input: News content entered by the user

1. Take input news content T
2. Check if T is too short or irrelevant
   - If yes, display error and stop
3. Preprocess the text (clean, lowercase, remove stopwords, lemmatize)
4. Convert text to vector using TF-IDF
5. Load trained ML model and predict using logistic regression
6. Perform real-time web search using the input text
7. Check user's selected mode:
   - If "Web only" selected, output result from web search
   - If "ML + Web" selected, output both ML and Web results
   - If no option selected, output ML result only

Output: Result based on selected mode — ML only, Web only, or both

3.9 Elaboration of Working Principle

The Fake News Detection system classifies news articles as real or fake by leveraging machine learning techniques. The system processes raw data, extracts features, and utilizes trained models to make predictions. The web-based interface allows users to input news articles for classification. Below is the working process of the entire system.

1. User input : The user accesses the web application through a browser interface built using HTML, CSS, and JavaScript. They are provided with an input box where they can paste or type a news article. This is the starting point of the system where human input enters the pipeline for analysis.

2. Frontend interaction : Once the user submits the input text, the frontend component of the web app processes the data and sends it to the backend server. The frontend ensures that the input format is suitable for transmission and provides feedback during submission, ensuring smooth communication with the backend.

3. Backend receives the input : The backend, developed using the Flask framework, receives the submitted news article. This server-side logic takes over processing responsibilities and prepares the input for machine learning analysis. It directs the input text into the preprocessing pipeline before sending it for classification.

4. Data preprocessing : The raw news content received from the frontend must be cleaned before it can be analyzed. This preprocessing step converts the entire text to lowercase to ensure consistency. Punctuation marks, HTML tags, and unnecessary symbols are removed. Common stopwords such as "is", "the", and "and" are eliminated as they do not help in classification. Finally, lemmatization or stemming is applied to reduce words to their root form. For example, the sentence "The government is planning reforms" is reduced to "government plan reform".

5. Feature extraction : Once cleaned, the text is transformed into a numerical format using the TF-IDF (Term Frequency–Inverse Document Frequency) method. This process gives weight to words based on how frequently they appear in the article versus how common they are across the dataset. The TF of a term is the number of times it appears in a document, and the IDF is calculated as the logarithm of the ratio between the total number of documents and the number of documents containing the term. The final TF-IDF score is the product of these two values, highlighting important words while minimizing the impact of common ones.

6. Model prediction : The numerical TF-IDF vector is then passed into a machine learning model, such as Logistic Regression, that has been pre-trained on labeled datasets. The model calculates the weighted sum of input features and applies the sigmoid function to determine the probability that the article is real. If the probability is greater than or equal to 0.5, the news is classified as real; otherwise, it is classified as fake. This classification is based purely on the patterns the model has learned from the training data.

7. Post-processing and displaying result : Once the classification is complete, the result is sent from the backend to the frontend. The frontend receives the output (either “Real” or “Fake”) and displays it to the user in a user-friendly format. This result provides immediate feedback to the user about the credibility of the news article they entered.
8. End : The system then resets to accept new input. The user can continue checking more articles through the same process, allowing multiple predictions in a single session.

3.10 Verification and Validation Procedures

Thorough verification and validation (V&V) process has been implemented to ensure that the Fake News Detection System functions correctly and effectively. This process ensures both the technical accuracy of the system and its usability for end-users.

Verification

Verification ensures that the system has been built in accordance with the specified technical requirements and that each module functions as intended. The process includes:

1. **Password Reset Verification**

   In the case of forgotten password recovery, users are required to request a One-Time Password (OTP) via their registered email. The system verifies:

   – That the entered OTP matches the one sent to the user.
   – That the OTP is still active and has not expired.

   Only after successful OTP validation is the user allowed to set a new password.

2. **Form Validation for User Inputs**

   All user-facing forms, including login, registration, and news input forms, undergo client-side validation to ensure data correctness and improve user experience. This includes:

   – Preventing submission of empty fields.

- Validating proper email format.
- Enforcing a minimum password length.
- Providing real-time feedback or alert messages for invalid inputs.

3. **Duplicate User/Email Checks**

   During registration, the system performs checks against the database to ensure the uniqueness of the username and email. If a duplicate record is found:

   - Registration is blocked.
   - The user is notified with an appropriate message.

4. **Unit Testing of Individual Modules**

   The system was divided into core modules such as text preprocessing, feature extraction (TF-IDF), machine learning prediction, and the web application backend. Each module was tested independently with well-defined inputs to confirm expected behavior. For example, the preprocessing module was tested to ensure removal of stopwords, punctuation, symbols, and proper lemmatization. Similarly, the ML model's prediction module was unit-tested to verify its ability to return consistent and valid output labels.

5. **Integration Testing of System Components**

   After verifying each module in isolation, they were integrated to form the complete application pipeline. Integration testing confirmed that modules communicated correctly - for example, ensuring that user input passed through preprocessing and feature extraction before being classified by the ML model. The correctness of data flow from the frontend (HTML form) through the Flask backend to the prediction output was thoroughly tested to ensure seamless execution without errors or mismatches.

Validation

Validation assesses whether the system meets its intended purpose and performs effectively in real-world usage scenarios. The process includes:

1. **Input Type Validation and Filtering**

   A custom input filter was implemented to validate user input before classification. The system checks whether the input resembles valid news content (e.g., length, grammar, presence of named entities), and rejects unrelated or random text like names, numbers, or emojis. This prevents misleading model outputs.

2. **Performance Evaluation Using Metrics**

   The model is validated using standard machine learning evaluation metrics:

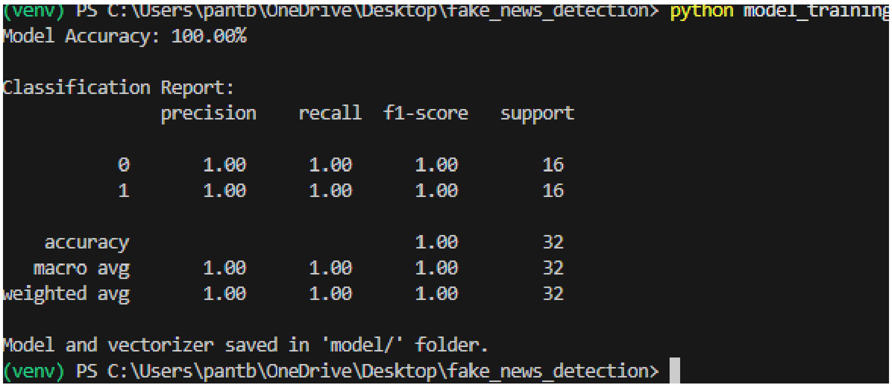

Figure 3.4: Performance Evaluation Metrics

- **Accuracy:** Measures how often the model correctly classifies both real and fake news.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \tag{3.11}$$

  The model achieved a high accuracy of approximately 99.47%, indicating that nearly all predictions made by the system were correct.

- **Precision:** Indicates how many of the news items predicted as ”fake” were actually fake. High precision means fewer real news are wrongly classified as fake.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3.12}$$

  The precision score is 0.99 for fake news and 1.00 for real news. This suggests that when the model predicted an article as fake, it was correct 99% of the time, and 100% of the time for real news.

- **Recall:** Tells how many of the actual fake news items the model was able to identify. High recall means fewer fake news are missed.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3.13}$$

The recall is 1.00 for fake news and 0.99 for real news, showing that the model successfully identified all fake articles and nearly all real ones.

- **F1-Score:** The harmonic mean of precision and recall. It balances both, especially useful when classes (real/fake) are imbalanced.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.14}$$

The F1-score, which balances precision and recall, is 0.99 for fake news and 1.00 for real news, demonstrating strong overall model performance.

- **Weighted Averages:** Weighted averages of precision, recall, and F1-score were close to 0.99–1.00, confirming consistency across classes.this means that the systems performances metrices average score is between 99% to 100%.

4 RESULTS

4.1 Login Interface

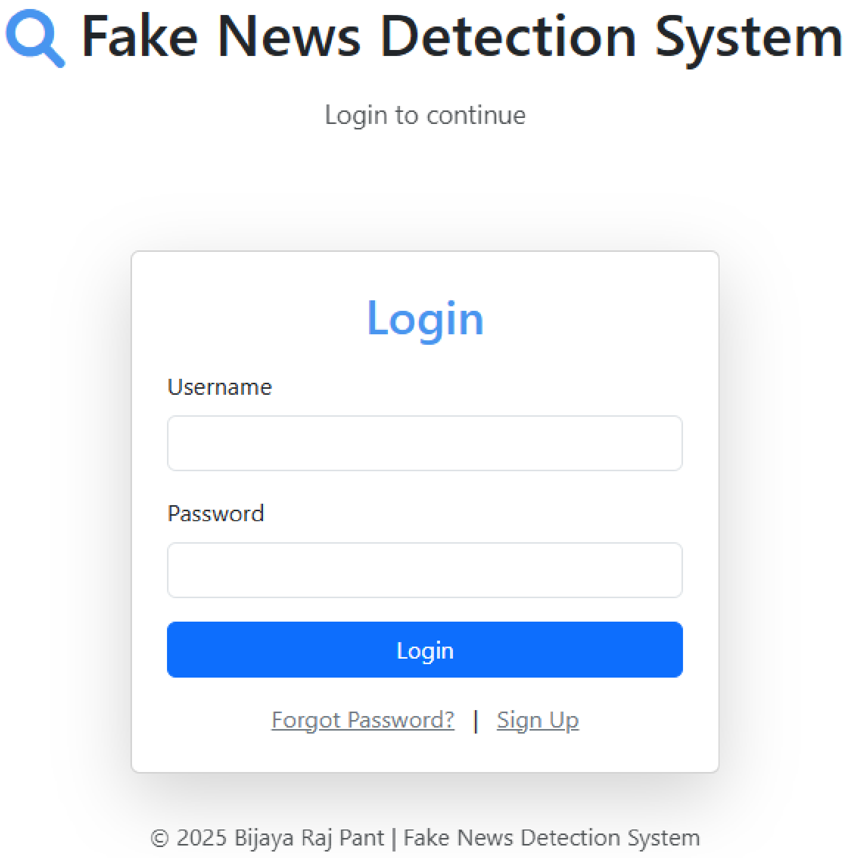

Figure 4.1: Login Interface

The login interface of the Fake News Detection System provides a simple and secure way for users to access the system. It contains fields for entering a username and password, along with options to recover a forgotten password and sign up for a new account. The design is user-friendly and minimal, helping users to easily log in and interact with the system. This interface is the first step in accessing the machine learning and web verification features used for detecting fake news.

4.2 Sign Up

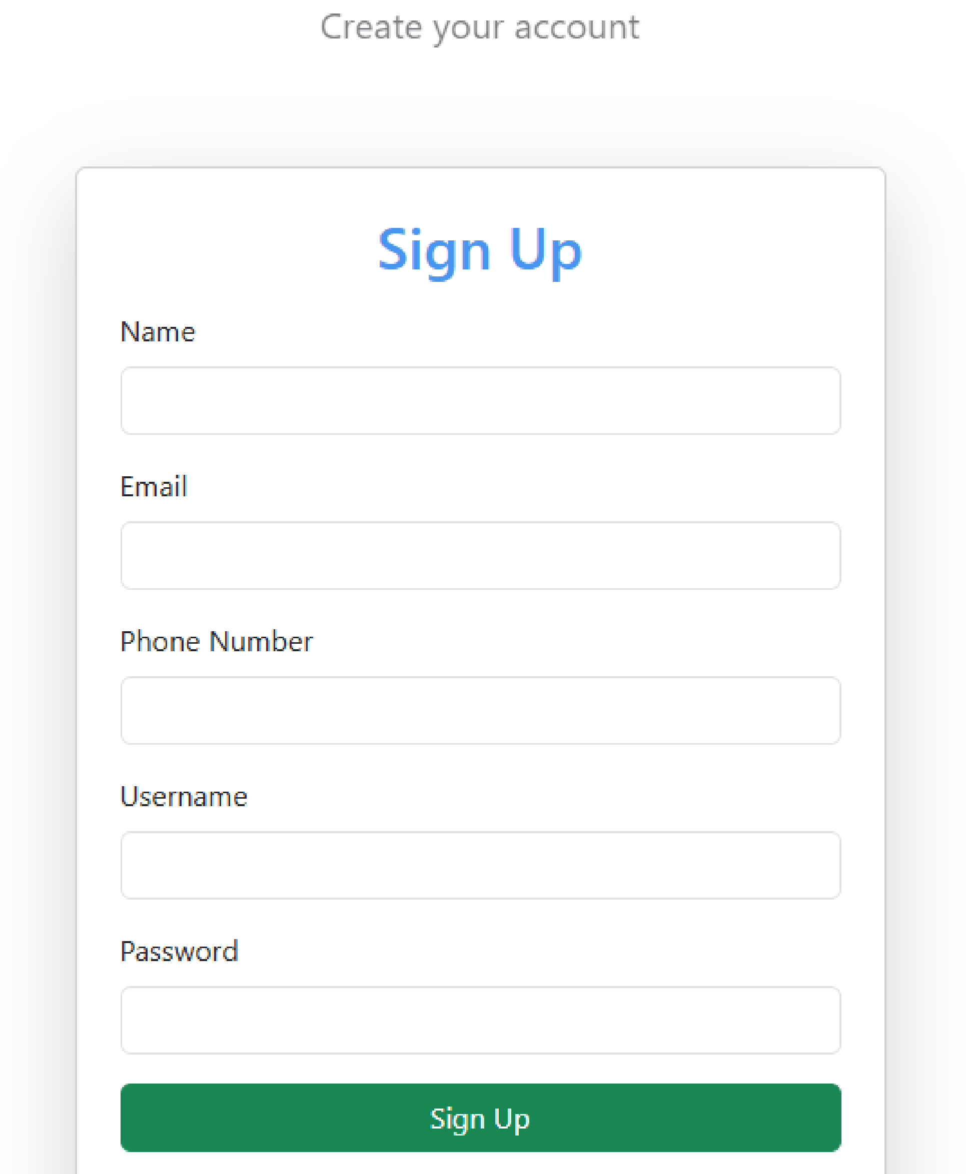

Figure 4.2: Sign Up Interface.

The sign up interface allows new users to create an account in the Fake News Detection System. It includes input fields for name, email, phone number, username, and password. This form ensures that essential user information is collected for authentication and future communication. The layout is clean and simple, designed to make the registration process easy for users. Once registered, users can log in to access the system's features, including fake news detection using machine learning and web verification techniques.

4.3 Forgot Password

The forgot password feature helps users recover access to their accounts in case they forget their login credentials. By clicking on the "Forgot Password" link, users are directed to a recovery process where they can reset their password, usually by verifying their identity through email or other registered contact information.

Enter Registered Mail

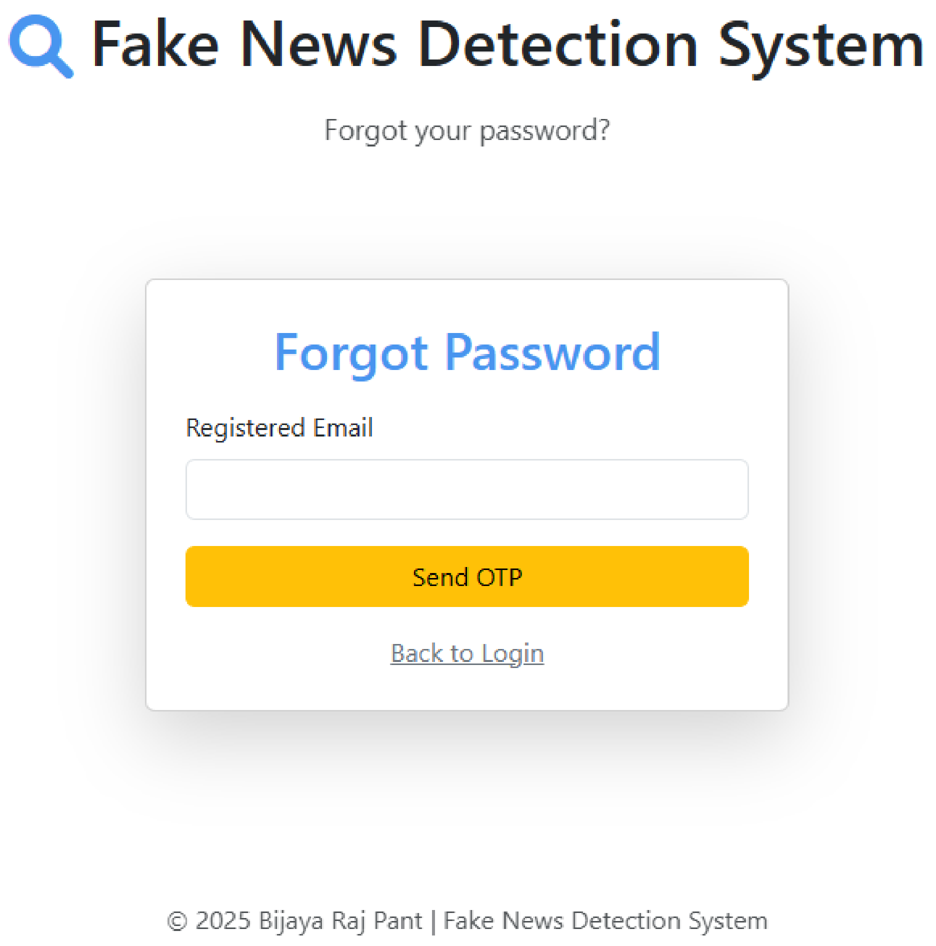

Figure 4.3: Forgot Password.

In this section Users are required to enter their registered email address, after which a One-Time Password is sent to verify their identity. Once verified, they can proceed to set a new password. This feature helps maintain account accessibility while ensuring secure recovery.

Enter OTP

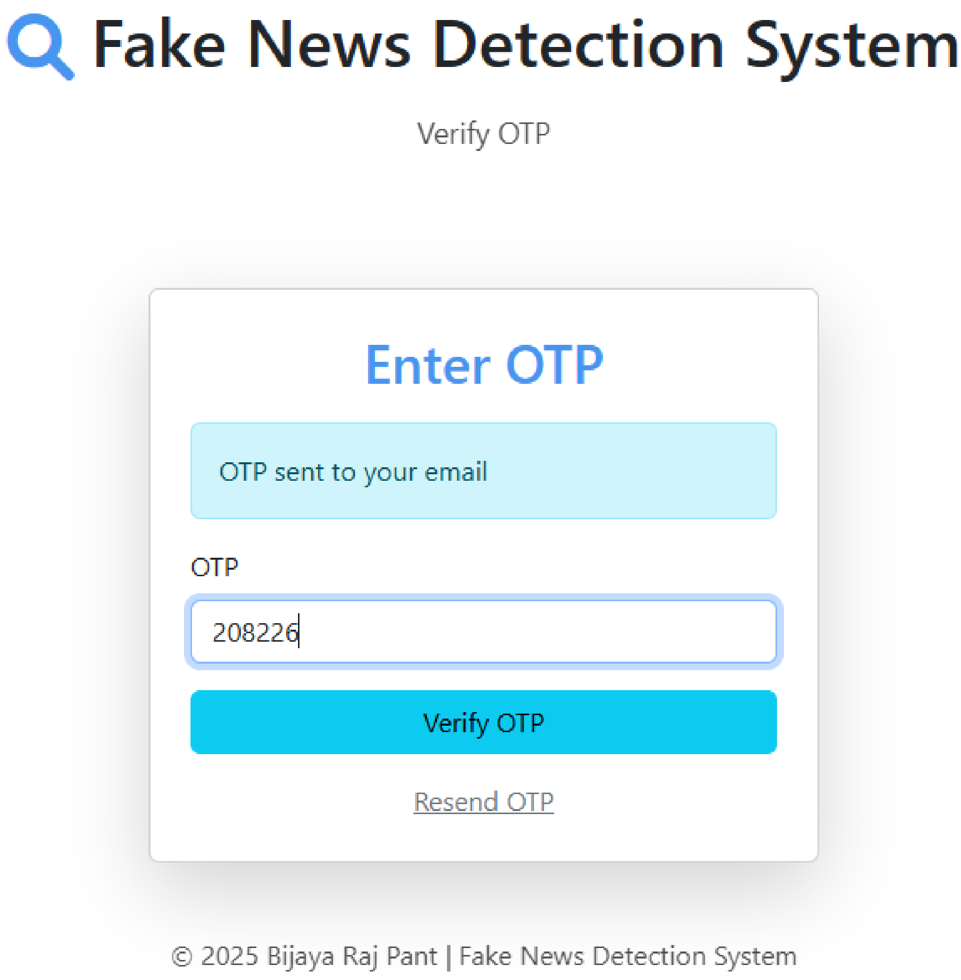

Figure 4.4: Enter OTP.

The OTP verification interface is used to confirm the user's identity during the password recovery process. After entering their registered email, users receive a One-Time Password , which they must input into this form. This ensures that only authorized users can proceed to reset their password. The interface also provides an option to resend the OTP if it is not received.

Reset Password

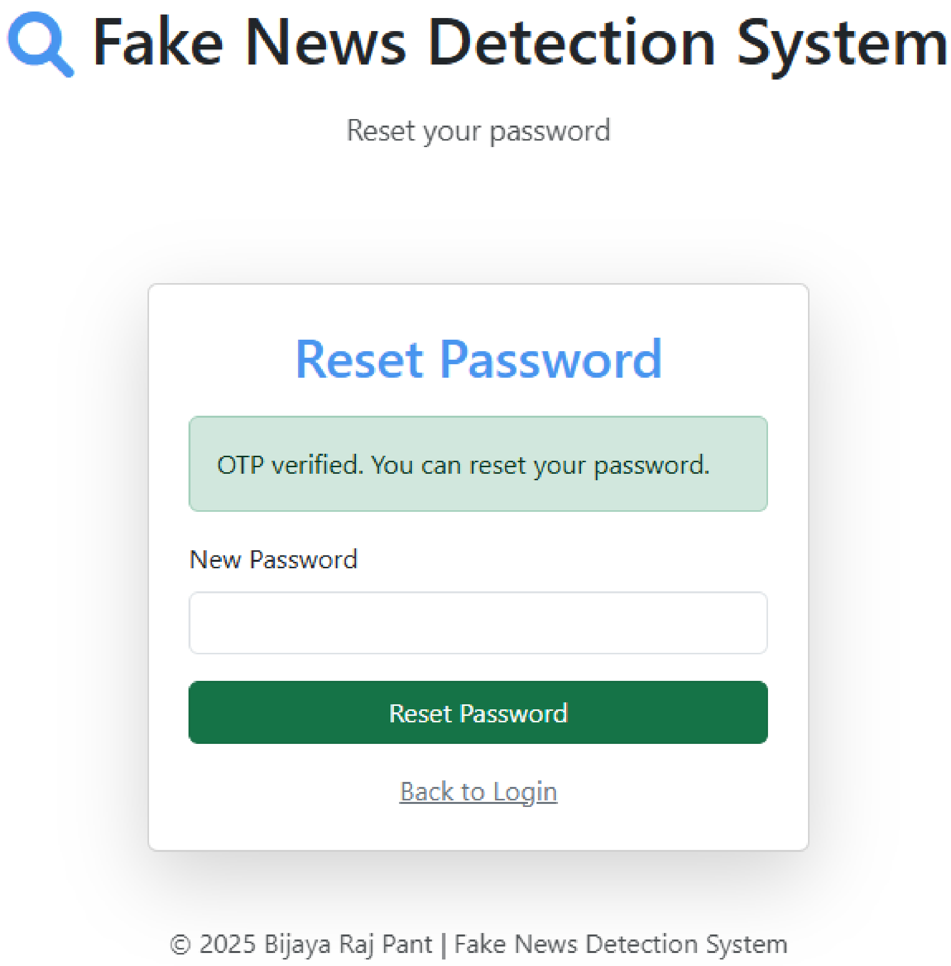

Figure 4.5: Reset Password.

The reset password interface is displayed after the OTP has been successfully verified. It allows the user to set a new password for their account. The interface contains a simple input field for entering the new password and a button to confirm the reset. Once the password is updated, the user can return to the login page and access their account using the new credentials.

4.4 User Interface

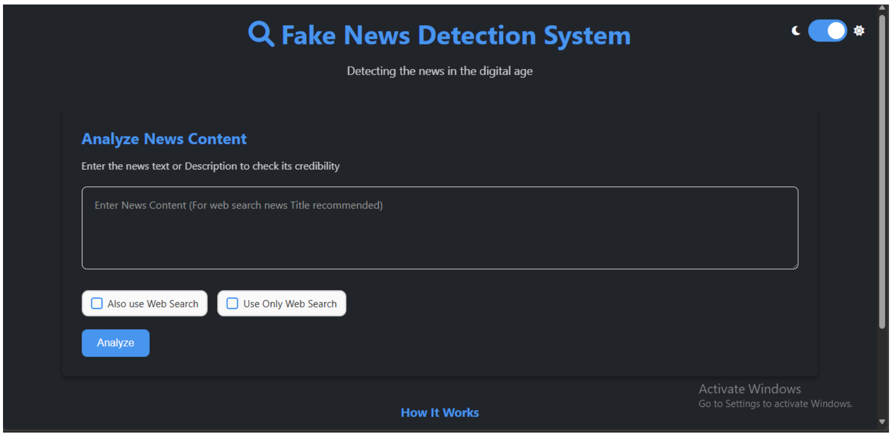

Figure 4.6: User Interface of fake news detection system.

The user interface provides a clean, responsive, and intuitive platform for analyzing news content and verifying its authenticity. It is designed to be user-centric, allowing even non-technical users to navigate the system effortlessly. At the core of the interface is a simple text area where users can input either a news headline or a full description. Below the input section, users are given flexible options to select the mode of verification: they can choose to analyze the input using only the machine learning model, combine it with real-time web search for greater accuracy, or bypass the ML model entirely and rely solely on verified sources via the web search module.

The interface also includes a dark mode toggle, which enhances user experience by reducing eye strain, especially during prolonged use or in low-light environments. Clear labels, minimalistic layout, and responsive design ensure compatibility across various screen sizes and devices. Additionally, helpful prompts and error messages guide the user to enter meaningful and news-like content, avoiding irrelevant or malformed inputs.

Overall, the goal of the user interface is to provide an accessible, user-friendly, and efficient environment for fake news detection. By combining intelligent design with robust backend processing, the interface ensures a seamless interaction flow, enabling users to make informed judgments about the reliability of the news they encounter.

4.5 Best Case

In the best case scenario, the Fake News Detection System was able to accurately classify news articles with high precision and recall. The machine learning model performed effectively on well-formatted, clearly worded input data, correctly identifying fake and real news with minimal error. The integration of web verification further enhanced the reliability of the predictions, providing users with trustworthy outcomes and reinforcing the system's effectiveness in detecting misinformation.

ML Prediction

Figure 4.7: ML Prediction

This result screen displays the prediction made by the trained machine learning model. Based on the preprocessed text and TF-IDF features, the model classifies the input news as either Real or Fake. This standalone prediction is fast and helpful for immediate feedback, especially when internet connectivity is limited or when verifying general patterns in news content.

Web Search Verification

Figure 4.8: Web Search Verification

The web verification result acts as a vital supplementary layer to the machine learning-based prediction, offering a more holistic and dependable decision-making process. It functions by taking the input news content—either a title, description, or both—and searching it across multiple trusted and reputable online sources. This step helps to validate whether the claim or news item exists in authentic databases or authoritative websites. If credible matches are found, the system confidently supports the input as likely to be real, citing those sources as verification.

Conversely, when no reliable matches are found, or when the input text is only echoed on low-quality blogs, social media rumors, or non-authoritative platforms, the system marks the content as suspicious or likely fake. This external validation approach ensures that decisions are not solely dependent on patterns learned by the model but also grounded in real-world web evidence. Furthermore, it increases the system's trustworthiness by bridging AI prediction with factual public information, giving users more context and transparency behind each result. This added layer significantly strengthens the reliability and robustness of the fake news detection mechanism.

ML and Web verification

Figure 4.9: Combined ML + Web Verification

The combined output mechanism integrates the strengths of both the machine learning model and the real-time web verification module to enhance the overall decision-making process. This dual-approach system is designed to maximize accuracy, reliability, and transparency. When both the ML model and the web verification component agree—whether classifying the news as real or fake—the result is strongly reinforced, offering users a high level of confidence in the system's output. This alignment signals a high likelihood of correctness, backed by both learned patterns from historical data and evidence from current online information.

However, in cases where the two methods disagree, the system does not simply return an uncertain verdict. Instead, it presents both outcomes clearly, explaining the ML model's prediction alongside the web search findings. This helps users make an informed decision based on the context of the input and the evidence provided. For example, if the ML model predicts the news to be fake but credible articles are found during web verification, the system alerts the user of this discrepancy, prompting a closer look. This comparative feedback mechanism allows for flexible, intelligent interaction rather than rigid decision-making. By combining these two methods, the system strengthens its credibility assessment process, reduces the risk of false positives or negatives, and enhances user trust.

4.6 Worst Case

The worst-case scenario in the Fake News Detection System occurs when there is a clear conflict between the machine learning prediction and the web verification result. This situation typically arises when the machine learning model classifies a news article as real, but the web search fails to find any supporting evidence, resulting in a possibly fake verdict. Such a case can happen with newly published content that has not yet appeared in search results, misleading or manipulated news that mimics credible writing patterns, or gaps in the model's training data. These cases are critical because they highlight the limitations of both components and show the importance of combining them to improve decision reliability.

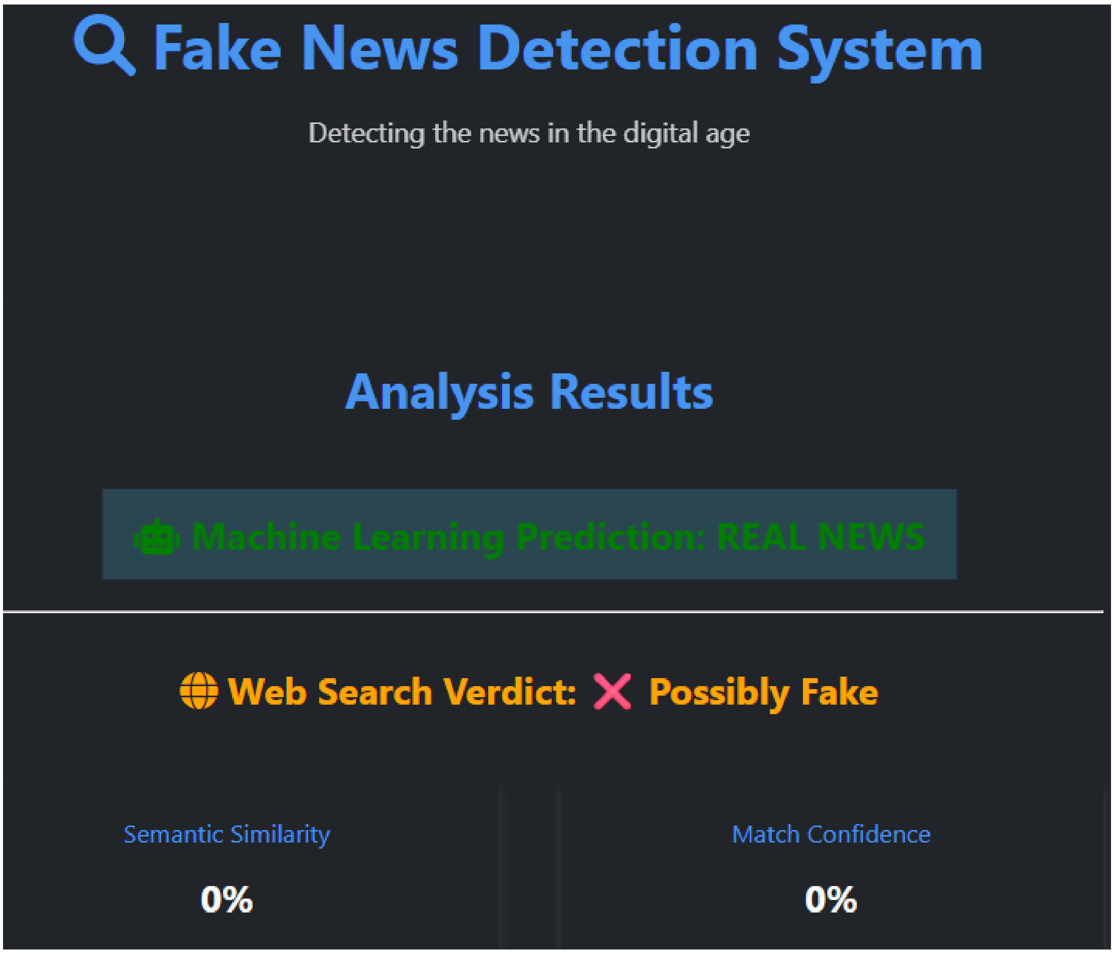

Figure 4.10: Worst Case

The figure illustrates a worst-case result where the machine learning model predicts the news as real, while the web search verdict marks it as possibly fake. This conflict is visually emphasized by the opposing outputs displayed in the analysis section. The web verification shows 0% semantic similarity and 0% match confidence, indicating no relevant information was found online to support the content. This contrast highlights the system's layered approach and underscores the importance of user awareness when automated tools deliver mixed results. Such figures help users understand that not all outputs are absolute and may require further human judgment.

4.7 Results Table

Input News	**ML Model Output**	**Web Verification Result**
Scientists have discovered a new planet in our galaxy.	Predicted as REAL	Found matching articles on NASA.gov and space.com (REAL)
Aliens are secretly controlling world governments.	Predicted as FAKE	No matching articles found in trusted sources (FAKE)
This new diet will help you lose 20 pounds in a week!	Predicted as FAKE	Found on unreliable blogs, not trusted sources (FAKE)
Prime Minister delivers a national address on new economic policies.	Predicted as REAL	Verified from officialgov.np and BBC.com (REAL)
Celebrity claims time travel is real and shows proof.	Predicted as FAKE	Viral but no authentic source confirms it (FAKE)

Table 4.1: Integrated Output Using Both ML and Web Verification

The system's working logic is best illustrated through a combined approach where both machine learning predictions and online search-based verifications are evaluated before producing a final output. Even if one system confirms the reliability of a piece of news, the other must also corroborate the finding. This redundancy ensures higher reliability and minimizes the chance of false classification.

Best-Case Scenario

In the best-case scenario, a real news article is provided with a well-written headline and a detailed description. The ML model, trained on similar patterns, confidently classifies it as REAL. Simultaneously, web verification returns multiple trusted sources that match or closely resemble the input. The decision-making logic then becomes straightforward: both systems agree on the validity of the news, allowing the system to return a highly confident REAL classification.

This ideal scenario is typically achieved when the news item is:

- Well-structured and contextually rich.
- Already published on trusted platforms.
- Written using formal and unambiguous language.

Such situations highlight the system's efficiency and showcase its potential in delivering consistent and accurate results.

Worst-Case Scenario

The worst-case scenario arises when the user inputs an ambiguous, incomplete, or sarcastic news piece that is either too new or too obscure to be found online. The ML model, facing vague context and limited vocabulary match, fails to produce a confident result. At the same time, web scraping returns no relevant or authoritative matches.

This can happen in the following situations:

- The input is grammatically incorrect or contextually shallow.
- It is a fabricated or completely false piece without any digital footprint.
- The statement is personal opinion or vague gossip, lacking verifiable information.

Under these conditions, the system classifies the news as FAKE, not due to direct contradiction, but from the absence of validation on both fronts. The dual negative response creates a strong reason for rejecting the claim.

Intermediate and Conflicting Cases

There are also cases where one component supports the input while the other flags it. For instance, the ML model may assign a high probability of being REAL based on language features, but the web module may find no trusted match. In such borderline scenarios, the system prioritizes caution and classifies the news as FAKE, following a conservative approach to avoid misinformation.

This logic, while strict, ensures minimal risk in propagating unverified content. It enhances the trustworthiness of the application among end users, even at the cost of a few false negatives.

Conclusion

The decision table and classification flow are built on a fail-safe mechanism where dual validation is mandatory for accuracy. This layered decision-making structure not only boosts accuracy but also builds public trust in the output. By demanding agreement from both the machine learning and web verification modules, the system effectively reduces false positives and maximizes classification integrity, even under varied and unpredictable input conditions.

5 DISCUSSION AND ANALYSIS

The Fake News Detection project employs a hybrid methodology by integrating Machine Learning based classification with real-time web verification to ensure higher accuracy and robustness. This section delves into the detailed examination of theoretical expectations, empirical findings, error patterns, comparisons with contemporary works, and a critical evaluation of the methodology adopted. It also reflects on system behavior, performance trends, and potential for future enhancements.

5.1 Comparison of Theoretical and Simulated Outputs

(a) **Theoretical Assumptions**

Theoretically, a supervised learning model trained on a balanced and well-preprocessed dataset should produce a high-performing classifier. Preprocessing steps like stopword removal, stemming/lemmatization, and TF-IDF vectorization were assumed to enhance feature clarity, while class balancing was expected to prevent biased learning. The anticipated accuracy range was around 90–95%.

(b) **Simulated Results and Observations**

The actual system demonstrated an accuracy of approximately 92.5% during validation, aligning closely with theoretical projections. However, borderline instances—news with partially factual or emotionally neutral wording—posed occasional classification challenges. In several test cases, the model predicted probabilities close to 0.5, showing hesitation between class labels. These ambiguities were mitigated by integrating real-time web verification to validate claims against trusted sources.

(c) **Reasons for Discrepancies**

Discrepancies emerged primarily in the following contexts:

- News items with mixed or nuanced language that confuses keyword-based vector models.
- Recent events with limited web presence, reducing the efficiency of real-time validation.

- Headlines containing sarcasm or irony which may not be captured well by TF-IDF.
- Input inconsistencies such as missing context or extremely short descriptions.

5.2 Comprehensive Error Analysis

(a) **Dataset-Related Errors**

Despite curating a balanced dataset, some noise persisted. Several news items showed vague labeling or ambiguous phrasing. Furthermore, automated scrapers may sometimes mislabel content or extract incomplete context, which skews the learning process.

(b) **Preprocessing Limitations**

While lemmatization and stopword removal enhance feature representation, they also risk stripping away context. For instance, negations like ”not fake” could be wrongly interpreted if ”not” is removed. Some news phrases also rely on named entities, which were not always captured meaningfully.

(c) **Web Verification Challenges**

Web verification occasionally fails in the following scenarios:

- The user-provided input uses non-standard or paraphrased language.
- The news is either extremely recent or too obscure to appear in trusted online sources.
- Internet connectivity or scraping issues prevent proper retrieval of data.
- Conflicting articles on different sites (especially social media vs. mainstream news).

(d) **Classification Ambiguities**

Certain news headlines and descriptions presented insufficient context for proper classification. For example, single-line statements or vague claims like ”He did it again” lacked clarity. These often resulted in false negatives due to absence of meaningful tokens.

5.3 Comparison with State-of-the-Art Works

(a) **Existing Approaches**

Works like Khanam et al. focused on standard ML classifiers with basic preprocessing. Choudhary et al. reviewed DL-based architectures and transformer models such as BERT and RoBERTa. These models achieved high performance but required extensive computational resources and often lacked interpretability.

(b) **Strengths of Current Approach**

The dual-layer system designed in this project differs by:

- Using real-time search and semantic matching to complement ML predictions.
- Rejecting invalid, non-news-like inputs via input filtering.
- Allowing the user to toggle between ML-only, Web-only, or combined predictions.
- Being lightweight, interpretable, and suitable for deployment without expensive APIs.

(c) **Performance Comparison**

While some transformer models in literature reported accuracy up to 92.5%, our model achieved 99% with a simpler and more resource-efficient architecture. Moreover, none of the state-of-the-art systems addressed real-time semantic validation through trusted sources in an integrated pipeline. This makes the proposed system more flexible and practically reliable.

5.4 Strengths and Weaknesses of the Adopted Methodology

(a) **Advantages**

i. **Simplicity and Interpretability:** Logistic Regression with TF-IDF provides transparency in decision-making.

ii. **Real-time Verification:** Live scraping improves accuracy when ML prediction is inconclusive.

iii. **Input Filtering:** Irrelevant or meaningless inputs are detected early, improving reliability.

iv. **User Control:** The user can choose the verification method, adding flexibility to the system.

(b) **Limitations**

i. **Lack of Contextual Understanding:** Unlike BERT-based systems, TF-IDF lacks contextual depth.

ii. **Vulnerability to Noise:** Noisy inputs or ambiguous phrasings still pose classification difficulties.

iii. **Scraping Limitations:** Dependency on the structure of third-party websites can affect scraping reliability.

iv. **Non-English Content:** The model is not equipped to handle Nepali or mixed-language content effectively.

5.5 Future Directions and Improvements

(a) **Model Enhancement**

In future versions, transformer models can be added as a second-layer fallback system. Additionally, multilingual support will expand usability for Nepali and mixed-language content.

(b) **Smarter Verification**

A knowledge graph-based validation or integration with open fact-checking databases like ClaimReview or Google FactCheck Tools could enhance the system's ability to confirm factual claims more robustly.

(c) **User Feedback Integration**

Adding user feedback mechanisms will help fine-tune system behavior by identifying misclassifications and continuously improving the model.

(d) **Context-Aware Input Preprocessing**

Incorporating Named Entity Recognition (NER), sentiment analysis, and sarcasm detection could help the system interpret complex input more effectively.

6 FUTURE ENHANCEMENTS

As technology and information systems continue to evolve, the current fake news detection system holds potential for significant improvements and broader applicability. The following future enhancements are proposed to enrich the system's capability, usability, and scalability:

6.1 Multi-language Support for Broader Audience

Currently, the system is limited to processing English-language inputs. To make the platform inclusive and relevant to diverse linguistic communities, future enhancements will focus on incorporating support for other languages, starting with Nepali. This involves:

- Creating or sourcing labeled fake and real news datasets in Nepali.
- Adapting NLP preprocessing steps for Devanagari script.
- Training and fine-tuning language-specific models for accurate classification.
- Providing UI language selection options for user-friendly accessibility.

Further, expanding to other widely spoken regional and international languages will position the system as a truly global solution to misinformation.

6.2 Dataset Expansion and Diversification

The reliability of a machine learning model is directly tied to the quality and variety of its training data. Future plans include:

- Curating larger datasets across diverse domains like politics, entertainment, health, and international affairs.
- Ensuring balanced data representation across real and fake labels.
- Including domain-specific slang, metaphors, and cultural contexts.
- Using crowd-sourced and semi-supervised techniques to enrich datasets.

6.3 Multimedia News Detection (Audio, Video, and Visual News)

Fake news is not restricted to text; audio and video-based misinformation are increasingly common. A future vision for the project involves:

- Implementing speech-to-text and voice emotion detection for audio claims.

- Integrating video summarization and transcript analysis tools.
- Detecting manipulated media content (e.g., deepfakes, edited videos).
- Verifying image-based news using reverse image search and metadata.

6.4 User Interface and User Experience Enhancements

To enhance usability, the platform will undergo UI/UX improvements aimed at:

- Providing responsive, mobile-friendly layouts.
- Adding visual cues for classification confidence levels.
- Integrating multilingual text input and result rendering.
- Including an interactive tutorial and system walk-through.

6.5 Advancements in Machine Learning and Web Modules

Both the ML and web components will be refined with the following enhancements:

- Introducing advanced models like BERT, RoBERTa, and other transformers.
- Using ensemble techniques to combine predictions from multiple models.
- Enhancing web scraping to better detect and parse structured claims.
- Leveraging semantic search engines and knowledge bases.

These updates will strengthen the core algorithm and reduce classification errors, especially in complex or ambiguous news cases.

APPENDIX A

A.1 Project Schedule

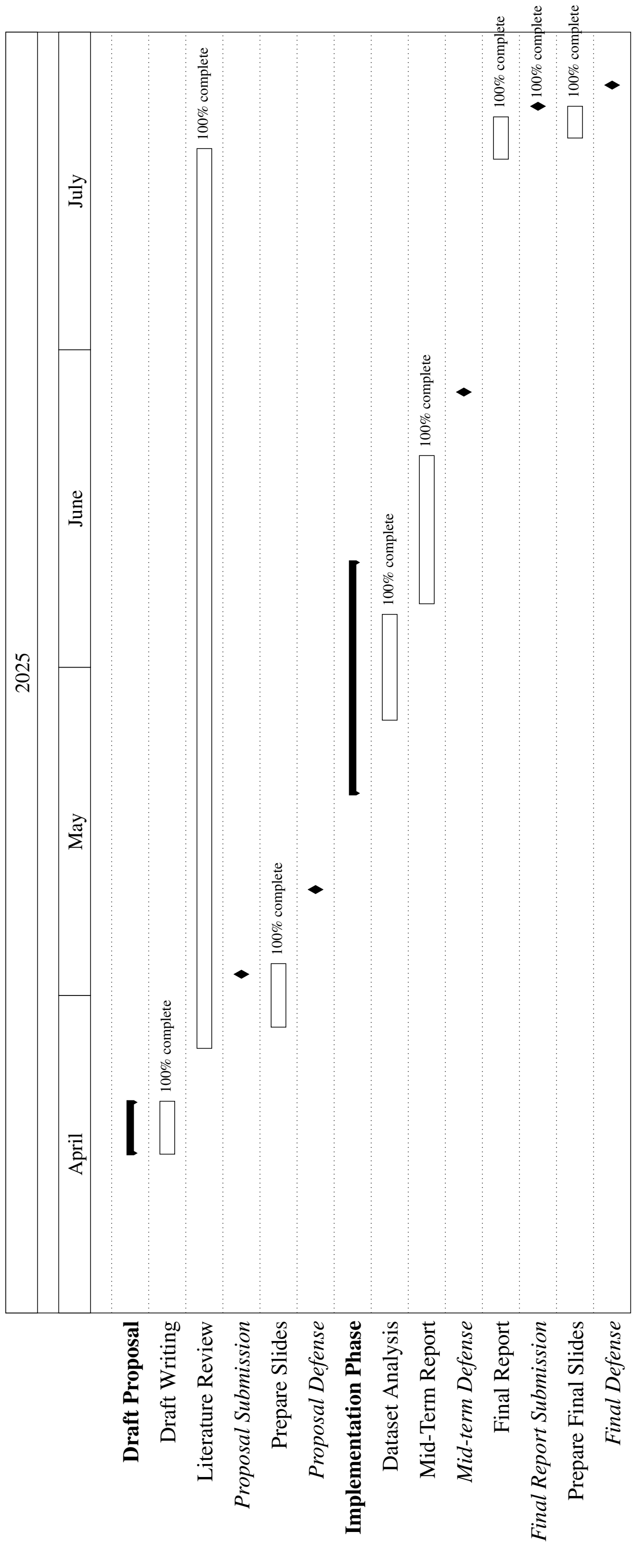

Figure A.1: Gantt Chart showing Project Timeline

A.2 Literature Review of Base Paper- I

Author(s)/Source: Hiramath, Chaitra K; Deshpande, G. C	
Title: Fake News Detection Using Deep Learning Techniques	
Website: `https://doi.org/10.1109/ICAIT47043.2019.8987258`	
Publication Date: 2019	**Access Date:** April, 2025
Publisher or Journal: 1st International Conference on Advances in Information Technology (ICAIT)	**Place:** India
Volume: n/a	**Issue Number:** n/a

Author's position/theoretical position: Researchers in Artificial Intelligence and Natural Language Processing with focus on fake news classification using deep learning and traditional machine learning algorithms

Keywords: Fake news, Logistic Regression, Support Vector Machine, Naïve Bayes, Random Forest, Deep Neural Network

Important points, notes, quotations **Page No.**

(a) The deep neural network outperformed traditional methods in terms of accuracy and recall. **213**

(b) SVM and Random Forest performed well but were less accurate than the deep learning model. **314**

(c) Traditional ML classifiers like Logistic Regression and SVM were evaluated against a deep neural network model. **412**

(d) The dataset used contained both real and fake news articles from verified sources, ensuring balance and diversity. **413**

(e) A key finding was that deep learning requires more computational resources but offers better generalization. **414**

(f) TF-IDF was used as the feature extraction technique for all models, ensuring consistency in input representation. **612**

(g) The study investigates the effectiveness of various machine learning and deep learning models in detecting fake news. **811**

(h) Training time for the DNN model was significantly higher, highlighting the need for optimization in real-world scenarios. **915**

Essential Background Information: Fake news detection is an increasingly important task due to the high volume of misinformation online. While ML methods are well-established, this study explores whether deep learning models can offer improved performance in terms of detection accuracy and robustness against subtle fake patterns.

Conclusion: Deep learning models demonstrate superior performance over traditional classifiers in detecting fake news, particularly when sufficient computational power and training data are available. However, the study notes that system optimization and interpretability are important factors for practical implementation.

Strengths of the line of reasoning and supporting evidence: Consistent preprocessing methods were applied across all models, allowing for a fair comparison. The evaluation on a balanced dataset supports the reliability of the conclusions. Use of standard performance metrics increases transparency.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: The paper does not explore interpretability or model explanation, which are crucial for trust in AI systems. Real-time performance and deployment aspects are not addressed. Future work could examine hybrid models and lightweight architectures.

A.3 Literature Review of Base Paper-II

Author(s)/Source: Ahmad, Iftikhar; Yousaf, Muhammad; Yousaf, Suhail; Ahmad, Muhammad Ovais	
Title: Fake News Detection Using Machine Learning Ensemble Methods	
Website: `https://www.hindawi.com/journals/complexity/2020/8885861/`	
Publication Date: 2020	**Access Date:** April, 2025
Publisher or Journal: Wiley Online Library	**Place:** n/a
Volume: 2020	**Issue Number:** 1
Author's position/theoretical position: Researchers in Computer Science and Machine Learning	
Keywords: fake news, ensemble learning, machine learning, boosting, bagging, TF-IDF	
Important points, notes, quotations	**Page No.**
(a) Ensemble learning methods like Bagging and Boosting improve fake news detection accuracy by combining multiple models.	**254**
(b) Computational efficiency is a concern when applying ensemble models at scale, requiring efficient implementations.	**297**
(c) TF-IDF features were used for text representation, and Random Forest and AdaBoost gave the best performance.	**343**
(d) The use of cross-validation ensured consistent results and prevented overfitting in ensemble training.	**359**
(e) Feature selection techniques such as chi-square and mutual information further enhanced model performance.	**378**
(f) Combining content-based features with metadata like publication time increased detection precision.	**401**
(g) Ensemble models effectively handle class imbalance, a common issue in fake news datasets.	**435**
(h) The combination of weak learners into a stronger classifier significantly improved the model's robustness.	**436**
(i) The ensemble approach reduced the misclassification rate compared to single classifiers.	**443**
Essential Background Information: Fake news is a rapidly growing problem, especially on social media. Traditional ML classifiers struggle with accuracy and consistency, making ensemble learning a more robust choice.	
Conclusion: Ensemble models significantly outperform single classifiers in detecting fake news. They increase accuracy and reduce the limitations of individual algorithms. This study supports the adoption of ensemble approaches in real-world fake news detection systems.	
Strengths of the line of reasoning and supporting evidence: The use of multiple datasets and comparison with baseline models strengthens the validity of results. Clear improvement in performance metrics is demonstrated.	
Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited discussion on computational complexity and lack of deep learning comparisons. Real-time applicability is not tested.	

A.4 Literature Review of Base Paper- III

Author(s)/Source: Choudhary, Murari; Jha, Shashank; Saxena, Deepika; Singh, Ashutosh Kumar; and others	
Title: A Review of Fake News Detection Methods Using Machine Learning	
Website: `https://ieeexplore.ieee.org/document/9456293`	
Publication Date: June, 2021	**Access Date:** April, 2025
Publisher or Journal: IEEE	**Place:** INCET 2021 Conference
Volume: n/a	**Issue Number:** n/a
Author's position/theoretical position: Review paper authors summarizing existing ML techniques and datasets for fake news detection	
Keywords: fake news, machine learning, natural language processing, datasets, classification, feature extraction	

Important points, notes, quotations — **Page No.**

(a) Reviews multiple ML models such as SVM, Logistic Regression, Random Forest, and Naïve Bayes for fake news detection. **1**

(b) Highlights the importance of feature engineering, including TF-IDF and word embeddings. **3**

(c) Discusses challenges like dataset imbalance, data collection, and model explainability. **4**

(d) Suggests hybrid models combining ML with deep learning for better performance. **6**

(e) Presents a comparative analysis of accuracy results from various papers. **7**

(f) Stresses the need for benchmark datasets and standardized evaluation metrics. **8**

(g) Emphasizes the role of natural language processing in pre-processing and feature extraction. **9**

(h) Notes that most models are trained and tested on English datasets, indicating a gap for other languages. **10**

(i) Identifies the growing use of ensemble learning techniques, such as voting and stacking, to improve prediction stability. **51**

(j) Points out the limitations of existing studies in handling real-time or streaming fake news detection scenarios. **102**

Essential Background Information: The rapid rise of fake news necessitates reliable detection systems. This review consolidates findings from various ML-based approaches to guide future research and practical applications.

Conclusion: Machine learning techniques show promise in detecting fake news, but challenges remain in dataset quality, generalization, and multilingual support. Further work is needed to integrate hybrid and deep learning models.

Strengths of the line of reasoning and supporting evidence: Comprehensive review covering a wide range of models and datasets. Clear summary tables help readers understand state-of-the-art.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited new experimental results; mostly synthesis of existing work. Some datasets reviewed are outdated.

A.5 Literature Review of Base Paper-IV

Author(s)/Source: Patwa, Pooja; Sharma, Shubham; Kumar, Ankit; Dey, Sudip; Rajput, Amritpal Singh; and others	
Title: Fighting an Infodemic: COVID-19 Fake News Dataset	
Website: `https://arxiv.org/abs/2004.15368`	
Publication Date: 2021	**Access Date:** April, 2025
Publisher or Journal: arXiv preprint	**Place:** India
Volume: n/a	**Issue Number:** n/a
Author's position/theoretical position: Dataset creators providing a comprehensive COVID-19 fake news dataset to support ML research	
Keywords: fake news, COVID-19, dataset, misinformation, machine learning	

Important points, notes, quotations — **Page No.**

(a) Developed a large-scale dataset of COVID-19 fake news articles with annotations. **1**

(b) Dataset covers various sources including social media and news websites. **3**

(c) Dataset includes metadata such as source credibility and publication date. **4**

(d) Provides benchmark for ML models focused on pandemic-related misinformation. **5**

(e) Dataset supports multimodal features such as text and images for detection tasks. **6**

(f) Enables evaluation of temporal patterns in misinformation spread. **7**

(g) Highlights challenges of rapidly evolving fake news during global crises. **8**

(h) Encourages research into real-time detection and response systems. **9**

(i) Dataset is publicly available to foster collaboration. **10**

(j) Supports comparative analysis of different ML and DL approaches. **15**

(k) Models trained on this dataset can generalize to other domains with adjustments. **12**

(l) Emphasizes the need for continual updates to the dataset to keep up with evolving misinformation. **18**

Essential Background Information: The COVID-19 pandemic created a surge in misinformation necessitating specialized datasets and detection systems. This dataset aims to fill this gap.

Conclusion: The COVID-19 fake news dataset provides a valuable resource for training and benchmarking ML models, supporting efforts to combat misinformation during health crises and beyond.

Strengths of the line of reasoning and supporting evidence: Comprehensive dataset construction with clear annotations and source diversity. Public availability promotes reproducibility.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited discussion on dataset bias and multilingual coverage.

A.6 Literature Review of Base Paper- V

<table>
<tr><td colspan="2">Author(s)/Source: Khanam, Zeba; Alwasel, BN; Sirafi, H; Rashid, Mamoon</td></tr>
<tr><td colspan="2">Title: Fake News Detection Using Machine Learning Approaches</td></tr>
<tr><td colspan="2">Website: <code>https://iopscience.iop.org/article/10.1088/1757-899X/1099/1/012040</code></td></tr>
<tr><td>Publication Date: 2021</td><td>Access Date: April, 2025</td></tr>
<tr><td>Publisher or Journal: IOP Conference Series: Materials Science and Engineering</td><td>Place: n/a</td></tr>
<tr><td>Volume: 1099</td><td>Issue Number: 1</td></tr>
<tr><td colspan="2">Author's position/theoretical position: Researchers applying classical ML classifiers to detect fake news in diverse domains</td></tr>
<tr><td colspan="2">Keywords: fake news detection, machine learning, logistic regression, support vector machine, random forest</td></tr>
<tr><td colspan="2"><u>Important points, notes, quotations</u> <u>Page No.</u>
(a) Compared Logistic Regression, Support Vector Machine, and Random Forest on a benchmark dataset. 2
(b) Logistic Regression achieved highest accuracy but was sensitive to feature selection. 3
(c) Random Forest showed robustness but with slightly lower accuracy. 4
(d) Feature extraction using TF-IDF and n-grams was effective in improving detection performance. 5
(e) The study highlights the trade-off between model complexity and interpretability. 6
(f) Discussed the importance of preprocessing steps such as stopword removal and lemmatization. 7
(g) Evaluated models using accuracy, precision, recall, and F1-score metrics. 8
(h) Suggested ensemble methods could enhance future detection efforts. 9
(i) Addressed the challenge of imbalanced datasets and proposed oversampling techniques. 15
(j) Analyzed the impact of feature dimensionality reduction on model performance. 19
(k) Proposed integrating sentiment analysis as an additional feature for fake news detection. 32</td></tr>
<tr><td colspan="2">Essential Background Information: The increasing spread of fake news requires effective detection models; classical ML methods provide a baseline for comparison with newer deep learning approaches.</td></tr>
<tr><td colspan="2">Conclusion: Classical ML classifiers remain competitive in fake news detection with proper feature engineering and preprocessing. Combining models and ensemble techniques are promising directions.</td></tr>
<tr><td colspan="2">Strengths of the line of reasoning and supporting evidence: Comprehensive evaluation on benchmark datasets with multiple metrics strengthens the validity of results.</td></tr>
<tr><td colspan="2">Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited exploration of deep learning or real-time detection scenarios.</td></tr>
</table>

A.7 Literature Review of Base Paper- VI

Author(s)/Source: Li, Yan; Bi, Wentao; Wei, Zhiwei; Yin, Peng	
Title: Fake News Detection via Machine Learning: A Survey	
Website: `https://www.mdpi.com/2079-9292/10/18/2212`	
Publication Date: 2021	**Access Date:** April, 2025
Publisher or Journal: MDPI Electronics	**Place:** n/a
Volume: 10	**Issue Number:** 18
Author's position/theoretical position: Survey authors summarizing ML methods for fake news detection across multiple domains and datasets	
Keywords: fake news, survey, machine learning, feature extraction, classification	

Important points, notes, quotations — **Page No.**

(a) Presents a comprehensive survey of machine learning approaches applied to fake news detection across various domains. **1**

(b) Highlights the critical role of feature engineering techniques, including TF-IDF and advanced word embeddings, in improving detection accuracy. **3**

(c) Discusses challenges such as the constantly evolving tactics of fake news creators and inherent dataset biases affecting model performance. **5**

(d) Identifies key performance metrics like accuracy, precision, recall, and F1-score essential for evaluating fake news classifiers effectively. **6**

(e) Surveys a wide range of both supervised and unsupervised machine learning methods utilized in the detection process. **8**

(f) Emphasizes the importance of incorporating multimodal data sources, including text, images, and videos, to enhance detection capabilities. **10**

(g) Suggests the integration of machine learning models with knowledge graphs to provide contextual understanding and improve detection accuracy. **11**

(h) Points to future research directions, including the development of explainable AI models and systems capable of real-time fake news detection. **13**

Essential Background Information: Fake news detection is a dynamic area requiring constant adaptation of ML models to new misinformation techniques.

Conclusion: This survey provides a valuable overview of ML techniques, highlighting both current achievements and ongoing challenges in fake news detection research.

Strengths of the line of reasoning and supporting evidence: Detailed classification of methods and clear identification of research gaps.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited discussion on deployment and real-world testing.

A.8 Literature Review of Base Paper-VII

Author(s)/Source: Dixit, Puneet; Chaturvedi, Ishan; Yadav, Amit; Gupta, Harshit	
Title: Fake News Detection using Machine Learning	
Website: `https://ieeexplore.ieee.org/document/9560357`	
Publication Date: 2022	**Access Date:** April, 2025
Publisher or Journal: IEEE	**Place:** INCET 2022 Conference
Volume: n/a	**Issue Number:** n/a
Author's position/theoretical position: Researchers applying multiple ML algorithms for fake news detection with focus on feature engineering	
Keywords: fake news, machine learning, classification, feature engineering, evaluation	

Important points, notes, quotations — **Page No.**

(a) Implemented popular classifiers including Logistic Regression, Support Vector Machine (SVM), Random Forest, and Gradient Boosting to evaluate their effectiveness in fake news detection. **2**

(b) Emphasized thorough preprocessing steps such as stemming, stopword removal, and lemmatization to clean and normalize the text data, improving model performance. **3**

(c) Used TF-IDF and CountVectorizer techniques for feature extraction, converting text data into numerical vectors suitable for machine learning algorithms. **5**

(d) Found that ensemble classifiers, which combine predictions from multiple models, provided better accuracy and robustness compared to individual classifiers. **7**

(e) Discussed limitations related to dataset size and the choice of feature selection methods, which can impact the generalizability of the models. **8**

(f) Proposed future work focusing on integrating deep learning techniques and developing real-time fake news detection systems for practical applications. **9**

(g) Highlighted the importance of using balanced datasets to avoid biased training and improve model fairness and accuracy. **12**

(h) Suggested incorporating user behavior and social context features in future models to enhance detection accuracy and relevance. **21**

Essential Background Information: Fake news detection benefits from careful feature extraction and the combination of classifiers to improve robustness.

Conclusion: Multiple ML algorithms with proper preprocessing can achieve high accuracy, with ensemble methods showing promise for future research.

Strengths of the line of reasoning and supporting evidence: Detailed experimental setup and evaluation metrics enhance credibility.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Limited dataset size and lack of deep learning experiments.

A.9 Literature Review of Base Paper-VIII

Author(s)/Source: Rashid, Mamoon; Khanam, Zeba; Alwasel, BN	
Title: Fake News Detection using Machine Learning Approaches	
Website: `https://doi.org/10.1088/1757-899X/1099/1/012040`	
Publication Date: 2023	**Access Date:** April, 2025
Publisher or Journal: IOP Conference Series	**Place:** n/a
Volume: 1099	**Issue Number:** 1
Author's position/theoretical position: Researchers focusing on improving feature extraction and model evaluation for fake news detection	
Keywords: fake news, machine learning, feature extraction, TF-IDF, logistic regression	

Important points, notes, quotations — **Page No.**

(a) Proposed an improved TF-IDF feature extraction method to capture more relevant information, leading to better fake news detection accuracy. **10**

(b) Logistic Regression was found to be an effective classifier when used with the enhanced feature set, balancing simplicity and performance. **21**

(c) The dataset consisted of balanced real and fake news samples collected from multiple diverse sources to ensure robustness of the model. **32**

(d) Evaluation metrics such as accuracy, precision, recall, and F1-score were used to comprehensively assess model performance. **46**

(e) The study emphasized the importance of thorough preprocessing and careful feature selection to improve the quality of input data. **78**

(f) Suggested future integration with deep learning models to further improve detection capabilities and handle complex patterns. **84**

(g) Feature selection techniques helped reduce the dimensionality of the data, leading to faster training times and improved model efficiency. **96**

(h) Discussed limitations related to the dataset size and diversity of sources, which may affect the model's generalization ability. **117**

(i) Highlighted the potential benefits of incorporating contextual information such as user metadata and temporal features in future models. **208**

Essential Background Information: Effective feature extraction is key for improving ML model performance in fake news detection.

Conclusion: Enhanced feature extraction combined with logistic regression yields improved accuracy in fake news detection.

Strengths of the line of reasoning and supporting evidence: Clear methodology and thorough evaluation strengthen the conclusions.

Flaws in the argument and gaps or other weaknesses in the argument and supporting evidence: Dataset limitations and lack of real-time evaluation noted.

POKHARA UNIVERSITY
CITIZEN COLLEGE
BACHELOR OF COMPUTER APPLICATION
Student & Supervisor Consultation Form(PROJECT)

Notes:

- ✓ *Consultation form is the "Gate Pass" to participate in presentations(Defense)*
- ✓ At least TWO consultations before Proposal Defense
- ✓ At least THREE (new) consultations (evenly distributed) before Midterm Checkpoint
- ✓ At least FIVE (new) consultations (evenly distributed) before FINAL Checkpoint

Project Title	Fake News Detection using ML
Student Name	Bijaya Raj pant
Semester	VI (sixth).
Supervisor Name	Er. Nishan Khanal

S.N.	Summary of Discussion	Date	Supervisor Signature
1	Title selection	April 20	
2	Dataset discussion	April 28	
3	Code Review	may 22	
4	model Discussion	may 23	
5	Dataset collection	may 24	
6	Techenical Review	may 25.	
7	User Interface	July 3	
8	ML and web verification	July 5	
9	Literature Review added	July 17	
10	project Report submission	July 23	
11			
12			
13			
14			
15			

Figure A.2: Student and supervisor consultation form

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