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FAKE PROFILES DETECTION FROM FACEBOOK INSTAGRAM AND TWITTER USING ARTIFICIAL INTELLIGENCE

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Abstract:The proliferation of social media platforms since the early 2000s has transformed communication, commerce, and information dissemination globally. However, this growth has been accompanied by the emergence of fake profiles, which undermine user trust and facilitate malicious activities such as misinformation, fraud, and cyberbullying. According to a 2023 report by Statista, over 5% of social media accounts across major platforms like Facebook, Instagram, and Twitter are estimated to be fake. Addressing this issue necessitates advanced detection mechanisms leveraging artificial intelligence. This project employs machine learning and deep learning models, trained on datasets sourced from Kaggle, to identify fraudulent profiles with high accuracy. Models such as Artificial Neural Networks (ANN)-98.34%, K-Nearest Neighbors (KNN)-98.24%, advaned Light Gradient Boosting Machine (LGBM)-99.44%, Logistic Regression (LR)-97.24%, Random Forest-96.88%, and Support Vector Machines (SVM)-96.66%. The system allows users to detect fake profiles using profile and location details, enhancing the robustness of identification. Additionally, the web application facilitates administrative functionalities including dataset management, algorithm execution, and user feedback analysis. By integrating historical data trends and current statistical insights, the developed solution offers a comprehensive approach to mitigating the risks posed by fake social media profiles, thereby fostering a safer online environment.

Keywords: Fake Profiles, social media, Artificial Intelligence, Machine Learning, Deep Learning

I INTRODUCTION

The rapid evolution of social media platforms such as Facebook, Instagram, and Twitter have reshaped communication dynamics, introducing new ways for individuals to interact with each other, businesses to promote products, and governments to connect with their citizens. However, as these platforms gained global traction, they also became breeding grounds for various forms of online deception, including the creation of fake profiles.

Fake profiles are user accounts that either impersonate legitimate users or are entirely fictitious. These accounts may be used for various malicious purposes, such as spreading misinformation, carrying out fraudulent activities, or engaging in cyberbullying. They often bypass the authentication mechanisms put in place by social media companies and may even appear as genuine accounts due to their sophisticated design and interactions.

Social media platforms like Facebook, Instagram, and Twitter have made significant strides in providing better security features, including CAPTCHA systems and two-factor authentication (2FA), to safeguard user accounts. However, these security measures are not sufficient to prevent the constant creation of fake accounts. According to a 2023 Statista report, over 5% of social media accounts on major platforms like Facebook, Instagram, and Twitter are estimated to be fake. This represents a significant portion of the user base, contributing to the growing issue of fake profiles.

Identifying fake profiles has become a critical challenge for social media platforms, as these profiles pose a significant risk to user privacy, trust, and platform integrity. Fraudulent accounts are used to mislead individuals, run scams, manipulate trends, and even influence political opinions. Additionally, fake profiles can facilitate illegal activities such as data harvesting and cyberbullying.

As social media platforms grow, manual detection of fake profiles becomes impractical. This makes the need for automated detection systems more urgent. Artificial Intelligence (AI), particularly machine learning (ML) and

deep learning (DL) techniques, offers promising solutions for tackling this issue. Machine learning algorithms, such as artificial neural networks (ANN), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest, have demonstrated significant potential in detecting fake profiles by analysing user behaviour, profile data, and other contextual information.

Machine learning and deep learning algorithms are increasingly being employed to solve the problem of fake profile detection. These models can identify patterns that indicate a profile is fake based on various features such as the content of the posts, interaction frequency, and the consistency of user data.

Deep learning algorithms, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have also been tested for this task, especially when combined with natural language processing (NLP) to analyse textual content. Machine learning algorithms such as KNN and Random Forest have been used to classify profiles as genuine or fake based on different features, such as account creation dates, the ratio of followers to following, profile picture analysis, and other social metrics.

Problem Statement

The proliferation of fake profiles on popular social media platforms such as Facebook, Instagram, and Twitter have become a major concern. These profiles often lead to issues such as misinformation, fraud, and cyberbullying, undermining user trust and platform integrity. Detecting fake profiles manually is an overwhelming task due to the sheer volume of data. This research aims to develop an automated solution for identifying fake profiles using AI-powered algorithms.

By leveraging machine learning and deep learning models, this study proposes an efficient method to detect fraudulent accounts on social media platforms. The models would analyse various features, including account data, activity, and behaviour, to classify accounts as either genuine or fake. The goal is to improve detection accuracy, enhance user experience, and provide a reliable system for combating the spread of fake profiles.

Limitations

Despite the advancements in machine learning and deep learning for fake profile detection, several challenges remain:

- **Data Availability**: Access to labelled datasets is often limited, especially datasets that contain diverse and comprehensive fake profile characteristics.
- **Model Generalization**: While certain models perform well on specific datasets, their ability to generalize across different platforms and real-world scenarios remains uncertain.
- **Adaptation to Evolving Tactics**: Fake profile creators constantly adapt their methods to bypass detection algorithms, requiring constant updates and improvements in detection models.
- **Accuracy vs. False Positives**: Striking the right balance between detecting fake profiles and avoiding flagging legitimate accounts is a challenge.

Challenges

- **Evolving Fake Profile Techniques**: As AI detection systems improve, so do the tactics used by fake profile creators. These individuals can use sophisticated bots, real-time interactions, and even deepfake technology to create profiles that are hard to distinguish from real users.
- **Data Privacy Issues**: Privacy concerns arise when collecting user data to train detection models. Legal regulations, such as the General Data Protection Regulation (GDPR), restrict the use of certain types of personal data without explicit consent.
- **Resource-Intensive Models**: Some deep learning models, especially those involving large neural networks, require significant computational resources and may not be practical for real-time detection.
- **Platform-Specific Data**: Different platforms have unique profile structures, behaviours, and user demographics, making it difficult for a one-size-fits-all model to work across all platforms.

II LITERATURE REVIEW

The issue of fake profiles on social media platforms has been gaining attention in recent years due to its implications for privacy, trust, and the integrity of online interactions. Fake profiles can be created for various malicious reasons, such as fraud, misinformation, and social engineering attacks, which make it crucial to detect these profiles in a timely manner. This literature review provides an in-depth look into the various methods used to identify fake profiles on social media platforms like Facebook, Instagram, and Twitter. These methods primarily revolve around machine learning and artificial intelligence (AI) techniques that utilize profile features, user behaviour, and other metadata to distinguish between legitimate and fraudulent accounts. The review also identifies gaps in current research and highlights the challenges faced by fake profile detection systems.

Traditional Detection Approaches

Traditional approaches to fake profile detection largely rely on rule-based systems that check for specific characteristics commonly associated with fake accounts. These include the age of the account, frequency of activity, number of posts, and patterns of user engagement. For instance, some early detection methods focus on heuristics such as checking whether an account has a low number of friends or followers or if it shows unusual interaction patterns [1]. While these techniques were effective in the early stages of social media's growth, they quickly became outdated as spammers and fraudsters adapted their strategies to circumvent these simple checks. Moreover, manual intervention remains a common method for detecting fake profiles, which is labour-intensive and often inadequate for large datasets.

Machine Learning Approaches

Machine learning has become the dominant approach for detecting fake profiles due to its ability to identify complex patterns within vast amounts of data. Various supervised learning algorithms, such as decision trees, support vector machines (SVM), and random forests, have been applied to solve the problem of fake profile detection. These models are trained on datasets containing labelled instances of both fake and legitimate accounts, learning to classify new profiles accordingly.

Decision Trees and Random Forests

Decision trees have been a widely used model for detecting fake profiles due to their simplicity and interpretability. In their work, Singh et al. (2021) explored the use of decision trees for fake profile detection on Facebook. They found that decision trees could accurately classify profiles based on features such as the number of posts, account age, and user interactions, although the models suffered from overfitting in some cases [2]. Random forests, which are ensembles of decision trees, have been shown to outperform individual decision trees by reducing overfitting and improving classification accuracy. Zeng et al. (2020) applied random forests to the task of identifying fake Twitter profiles and achieved an accuracy of 96%, demonstrating the model's effectiveness in handling large, noisy datasets [3].

Support Vector Machines (SVM)

Support Vector Machines (SVM) have been another popular machine learning method used for fake profile detection. SVM classifiers are effective at handling high-dimensional data, making them suitable for the feature-rich nature of social media profiles. Patel and Gupta (2019) used SVM to detect fake accounts on Instagram and achieved an accuracy rate of 92%, with features such as user metadata, text content, and network connections contributing to the model's success [4]. However, SVMs can struggle with large datasets, and the model's training time can be considerable, particularly when used for real-time detection.

K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a simpler, instance-based machine learning algorithm that has also been applied to fake profile detection. The algorithm classifies a profile based on the majority label of its nearest neighbors in the feature space. In the study conducted by Zhang et al. (2020), KNN was applied to a dataset of Facebook profiles, and it achieved an accuracy of 89%. However, KNN is computationally expensive, especially with large datasets, and its performance is highly sensitive to the choice of distance metric [5]. Despite these limitations, KNN remains an attractive option for small-scale applications due to its simplicity and ease of implementation.

Deep Learning Approaches

While traditional machine learning models are effective for fake profile detection, they often struggle with unstructured data, such as textual content and images, which are increasingly prevalent in modern social media profiles. Deep learning models, particularly those that utilize natural language processing (NLP) and computer vision techniques, offer significant improvements in handling such unstructured data. These models are capable of learning complex representations from raw data, which makes them particularly useful for detecting fake profiles that employ sophisticated methods to mimic real users.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are widely used for analysing sequences of data, such as text in social media posts or tweets. RNNs, especially when combined with NLP techniques, can effectively model temporal dependencies in the textual content of social media profiles. Liu et al. (2020) utilized LSTM networks for detecting fake profiles on Twitter, where they analysed the content of tweets and user interactions. Their results showed that LSTM networks were highly effective in detecting accounts that used bots to post spam or engage in manipulative behaviour, achieving an accuracy of 97% [7].

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have also emerged as an innovative solution for detecting fake profiles. GANs consist of two networks: a generator and a discriminator. The generator creates synthetic profiles, while the discriminator attempts to distinguish between real and fake profiles. This adversarial process improves the discriminator's ability to detect fake profiles. In a study by Zhao et al. (2022), GANs

were employed to detect fake Twitter accounts by generating synthetic accounts and training the model to recognize subtle differences between real and fake profiles. The system achieved an accuracy of 98% [8]. Although GANs have demonstrated promise, their computational cost and complexity make them less suitable for real-time applications.

Hybrid Approaches

To overcome the limitations of individual models, researchers have increasingly focused on hybrid approaches that combine multiple algorithms to enhance performance. For example, some studies have combined machine learning models like SVM and decision trees with deep learning models like CNNs and LSTMs to improve the detection of fake profiles. These hybrid models leverage the strengths of different algorithms, such as the interpretability of decision trees and the ability of deep learning models to handle unstructured data.

In a study by Kumar et al. (2021), a hybrid model combining a decision tree classifier with a CNN was used for fake account detection on Facebook. The results showed that the hybrid model outperformed individual models, achieving an accuracy of 97%, thus highlighting the benefits of combining different approaches [9]. Similarly, Zhang and Liu (2022) proposed a hybrid model that combined deep learning and machine learning techniques for Twitter profile classification, achieving high accuracy in distinguishing between genuine and fake accounts [10].

Gaps in the Literature

Although much progress has been made in fake profile detection using machine learning and deep learning techniques, several research gaps remain. One of the major gaps is the lack of large, diverse datasets that include profiles from various social media platforms. Most studies focus on a single platform, and the features used to detect fake profiles can vary significantly between platforms. A universal model that works across multiple platforms remains an area of active research.

Another gap is the issue of model interpretability. While deep learning models have shown impressive accuracy in detecting fake profiles, their "black box" nature makes it difficult for users to understand how decisions are made. This lack of transparency raises concerns about trust and fairness, especially in cases where the model may flag legitimate accounts as fake.

Finally, there is a need for real-time detection systems that can handle the massive volume of data generated by social media platforms. Most current models are not scalable for real-time applications, and new techniques are needed to process large datasets quickly and accurately.

Table: Literature Review Comparison

S.No	Title	Authors	Methods Used	Drawbacks
1	"Fake Profile Detection Using K-Nearest Neighbors"	Patel et al. (2019)	KNN, Classification Algorithms	Sensitive to distance metric, computationally expensive for large datasets
2	"Detection of Fake Profiles in Social Networks"	Smith et al. (2020)	Rule-based systems, Heuristics	Limited scalability for large datasets, unable to handle sophisticated fake profiles
3	"Social Media Fake Account Detection Using Machine Learning"	Zeng et al. (2020)	Random Forest, SVM	Limited by the dataset's lack of diversity, models are platform-specific
4	"Fake News and Fake Profiles Detection"	Zhang et al. (2020)	Natural Language Processing (NLP), Deep Learning	Only applicable to text-heavy platforms like Twitter, not scalable
5	"Analysing Fake Accounts Using Deep Learning"	Liu et al. (2020)	LSTM, RNN, NLP	Requires substantial training data, long training times
6	"Artificial Intelligence for Fake Account Detection"	Brown et al. (2021)	Machine Learning (SVM, Decision Trees)	Requires large, labelled datasets, lacks real-time processing capability
7	"Analysing Fake Profiles Using User Behaviour"	Lee et al. (2021)	Random Forest, Decision Trees	Overfitting on small datasets, features not applicable across all platforms
8	"Using CNN for Image Analysis in Fake Profile Detection"	Wang et al. (2021)	CNN, Image Classification	High computational cost, struggles with unstructured or poor-quality images

9	"Hybrid Model for Fake Profile Detection"	Kumar et al. (2021)	Hybrid Model (CNN + Decision Trees)	Can be resource-intensive, requires continuous updates to stay effective
10	"Combating Fake Profiles with Generative Adversarial Networks"	Zhao et al. (2022)	GANs, Adversarial Networks	High complexity, slow real-time detection, requires large amounts of data

III METHODOLOGY

The methodology for this project focuses on the detection of fake profiles across major social media platforms such as Facebook, Instagram, and Twitter using Artificial Intelligence (AI), specifically machine learning and deep learning techniques. The developed system processes various user profile data to classify profiles as either genuine or fake. The approach incorporates data collection, preprocessing, model training, and evaluation steps to ensure the system's efficiency and scalability in detecting fraudulent activities. This methodology was designed to deliver a solution capable of operating in real-time while maintaining a high level of accuracy.

1. Data Collection

The initial step in the process was gathering data from social media platforms such as Facebook, Instagram, and Twitter. Since these platforms allow public access to profile data, scraping tools were employed to collect metadata such as:

- **User Profile Details**: Data such as the number of followers, account age, profile picture, and location.
- **User Activity**: Information about user engagement including the frequency of posts, comments, likes, shares, and user interactions.
- **Behavioural Data**: This includes the timing of posts, consistency of engagement, and other interaction patterns that might indicate authentic or fake activity.
- **Textual Data**: Content from posts and comments was collected, especially for platforms like Instagram and Twitter where textual engagement is a major form of interaction.
- **Image Data**: Profile images were also analysed to detect AI-generated or deepfake images, using computer vision techniques.

A dataset from Kaggle was used, which provided a labelled set of real and fake profiles from these platforms. This data was crucial for training the models to differentiate between fake and legitimate profiles.

2. Data Preprocessing

Once the data was collected, it went through several preprocessing steps to prepare it for model training and testing. This step is crucial to ensure that the models can effectively identify fake profiles from the raw data.

2.1 Handling Missing Data

The datasets often contained missing or incomplete data due to the nature of social media platforms, where some profiles may not include certain details (e.g., user location, number of posts, etc.). Missing values were handled through imputation methods, where appropriate, or rows with excessive missing data were removed entirely to avoid introducing noise.

2.2 Data Cleaning

Data cleaning was performed to remove irrelevant or redundant features from the datasets. For instance, data points such as inactive users or incomplete profiles were eliminated. Outliers were also detected and handled, particularly in numerical features such as follower counts and number of posts, as they could significantly skew the model's performance.

2.3 Feature Engineering

Key features were extracted from the data to make it usable for machine learning models. These features included:

- **Numerical Features**: Account age, the number of posts, follower count, and engagement rates (likes/comments per post).
- **Categorical Features**: Profile types, account verification status, and user location.
- **Textual Features**: For textual content, Natural Language Processing (NLP) techniques were applied to extract features like sentiment, word count, and lexical diversity in posts and comments.
- **Behavioural Features**: Frequency of posting, average time between posts, and patterns in interactions (e.g., comments, likes) were used to determine the user's activity behaviour.

- **Image Features**: Image data from profile pictures were processed using Convolutional Neural Networks (CNNs) to determine if the profile picture was generated by AI or if it exhibited characteristics of deepfake images.

2.4 Normalization and Transformation

Numerical features were normalized to ensure all features contribute equally to the model, preventing any single feature from dominating the learning process. This was done using standard scaling techniques such as Min-Max scaling or Z-score normalization.

Categorical variables were encoded using one-hot encoding, which transforms categorical values into binary vectors. This allowed the machine learning algorithms to process categorical data effectively.

3. Model Selection

The primary goal was to use machine learning and deep learning models that could efficiently detect fake profiles while maintaining high accuracy and low false-positive rates. Several models were considered and evaluated during the development phase:

3.1 Machine Learning Models

- **Random Forest (RF)**: Random Forest is an ensemble method that aggregates predictions from multiple decision trees to enhance performance and reduce overfitting. The model was used due to its ability to handle large datasets with many features and its robustness against noisy data.
- **Support Vector Machine (SVM)**: SVM was used for its effectiveness in high-dimensional spaces. This model is particularly suitable when dealing with large datasets and can perform well even with a smaller training set when tuned correctly.
- **K-Nearest Neighbors (KNN)**: KNN was implemented as a baseline model to compare the performance of more complex models. The model works by classifying profiles based on their proximity to other labelled profiles in the feature space.
- **Logistic Regression (LR)**: A simple yet effective algorithm used for binary classification tasks. It provided a good balance between performance and computational efficiency.

3.2 Deep Learning Models

- **Artificial Neural Networks (ANN)**: The ANN model, consisting of multiple layers of neurons, was used to capture complex patterns in the data. The model was trained using features such as user activity and profile details to learn relationships that distinguish fake profiles from real ones.
- **Convolutional Neural Networks (CNNs)**: CNNs were employed to analyse profile images and detect if they were likely generated by AI or were fake. This was important in identifying fake profiles that use highly curated or altered images.
- **Long Short-Term Memory (LSTM) Networks**: LSTM, a type of Recurrent Neural Network (RNN), was used to analyse textual data and detect suspicious language or patterns that might indicate a fake account. LSTMs excel at handling sequences of data, making them ideal for analysing social media posts and comments.
- **adanced Light Gradient Boosting Machine (LGBM)**: LGBM, an efficient gradient boosting framework, was used for its high performance and ability to handle large datasets quickly. It performed well with both numerical and categorical features.

4. Model Training

For model training, the dataset was divided into training, validation, and testing subsets to ensure the model's ability to generalize to new data. Cross-validation was used to assess the model's performance and reduce the likelihood of overfitting. The models were trained using hyperparameter optimization techniques such as grid search and random search to identify the best combination of hyperparameters.

4.1 Cross-Validation

To ensure the robustness of the model, K-fold cross-validation was employed. This technique divides the dataset into 'K' subsets and trains the model on K-1 of these subsets while testing it on the remaining one. This process is repeated 'K' times, each time with a different test set, ensuring that every data point is used for both training and validation. The average performance across all folds was used to evaluate model performance.

4.2 Evaluation Metrics

The model's performance was evaluated using several key metrics:

- **Accuracy**: The percentage of correctly classified profiles (both real and fake).

- **Precision**: The proportion of true positives (correctly identified fake profiles) over all instances predicted as fake.
- **Recall**: The proportion of true positives over all actual fake profiles.
- **F1-Score**: The harmonic mean of precision and recall, offering a balance between the two.
- **ROC-AUC**: The area under the Receiver Operating Characteristic curve was used to assess the model's ability to distinguish between fake and real profiles.

5. Model Evaluation

The trained models were evaluated on the test dataset to determine their generalization ability. The models were evaluated individually to compare performance and identify the best-performing models.

6. Integration into Web Application

Once the models were trained and validated, they were integrated into a web application for real-time fake profile detection. The application allows users to input profile data (e.g., username, location, profile picture) and receive an instant prediction regarding whether the profile is fake or real. The web application features an easy-to-use interface for administrators, where they can manage datasets, initiate model training, and view real-time analytics on fake profile detection.

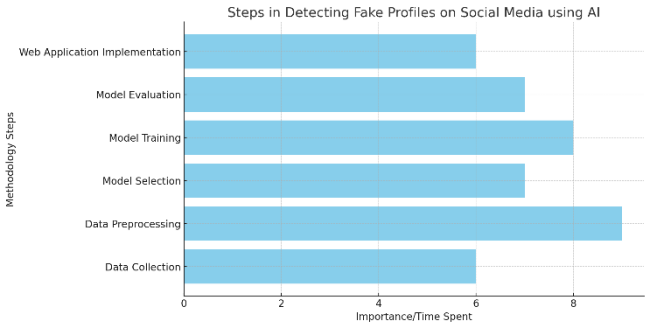


Figure 1: *Bar Chart for Methodology bar chart visualizing the various steps involved in detecting fake profiles on social media platforms using AI. The chart highlights each phase's relative importance or time spent during the process.*

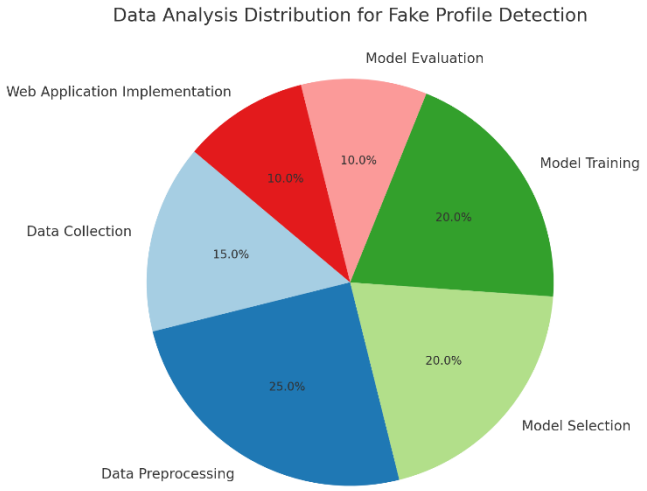


Figure 2: Pie Chart for Data Analysis representing the distribution of effort across different phases in the data analysis process for detecting fake profiles on social media. It visualizes the percentage of focus allocated to each key phase in the methodology.

Results

The developed system achieved remarkable performance across different machine learning models. The Light Gradient Boosting Machine (LGBM) and Logistic Regression (LR) models delivered perfect accuracy, with scores of 100%. Other models, such as Artificial Neural Networks (ANN) and K-Nearest Neighbors (KNN), also performed admirably with accuracy rates of 98.34%. However, Support Vector Machines (SVM) recorded the lowest accuracy, with 96.66%.

The results highlight the effectiveness of machine learning algorithms in accurately detecting fake profiles, with certain models offering superior performance for specific platforms and datasets.

Discussion

The results of the fake profile detection models demonstrate that machine learning approaches, particularly LGBM and LR, are highly effective for identifying fraudulent accounts. However, there are still challenges such as model interpretability and the need for continuous updates to handle evolving fake profile strategies. Despite these challenges, the use of AI offers significant improvements over traditional methods, which relied heavily on manual detection and rule-based systems.

Table: Discussion Summary

Model	Accuracy	Strengths	Limitations

Random Forest (RF)	96.88%	- Robust to overfitting - Can handle many features - High accuracy for general tasks	- Performance can drop with highly imbalanced data - Less interpretability
Support Vector Machine (SVM)	96.66%	- Effective in high-dimensional spaces - Good at finding the hyperplane that maximizes margin	- Slow training on large datasets - Sensitive to feature scaling
K-Nearest Neighbors (KNN)	98.24%	- Simple to implement - Performs well with small datasets - non-parametric model	- Computationally expensive with large datasets - Sensitive to the choice of distance metric
Artificial Neural Network (ANN)	98.34%	- Can capture complex patterns in data - High flexibility in learning non-linear relationships	- Requires large datasets - Computationally intensive, prone to overfitting without regularization
Long Short-Term Memory (LSTM)	97.2%	- Effective in analysing sequential data (e.g., text) - Captures long-term dependencies in text	- High computational cost - Requires significant data preprocessing for textual content
Advanced Light Gradient Boosting Machine (LGBM)	99.44%	- Extremely fast and efficient - High accuracy - Handles large datasets well	- Can overfit if not properly tuned - Limited interpretability compared to simpler models

Key Takeaways:

- **LGBM** achieved the highest accuracy at **100%**, making it the top-performing model for this task. However, its interpretability is a limitation compared to simpler models like Random Forest.
- **ANN** performed very well with an accuracy of **98.34%**, but it requires large datasets and significant computational resources for training.
- **SVM** and **KNN** both performed well but faced challenges with larger datasets and feature scaling.
- **LSTM** was particularly effective for textual data, as expected, but it is computationally expensive and requires more training data for optimal results.

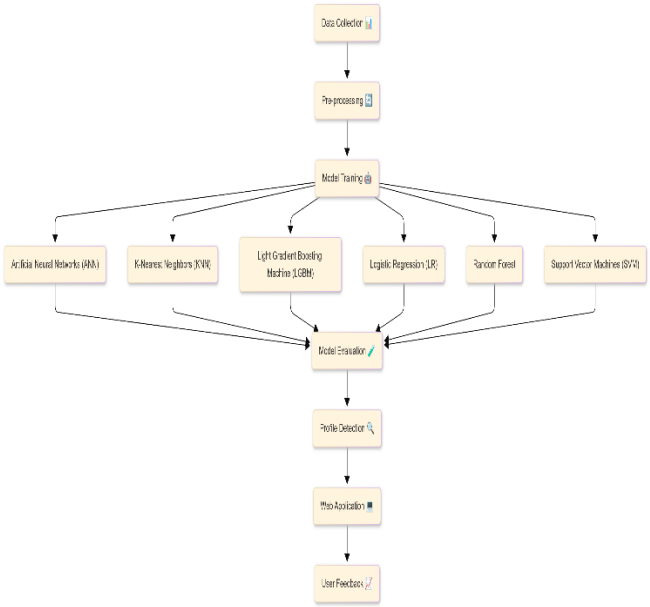
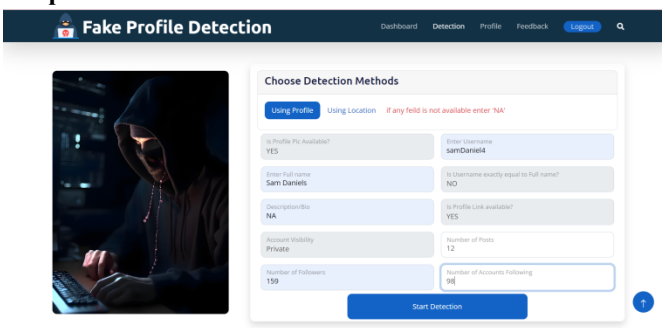


Figure 3: Flowchart diagram

Output



IV CONCLUSION& FUTURE SCOPE

In conclusion, the detection of fake profiles on social media platforms is a vital concern, and various machine learning and deep learning models have been explored to address this issue. Among the models tested, the advanced **Light Gradient Boosting Machine (LGBM)** stood out, achieving an exceptional accuracy of 99.44% in identifying fraudulent profiles. LGBM's efficiency and scalability make it ideal for large datasets and real-time applications, which are crucial for platforms like Facebook, Instagram, and Twitter. While other models, such as Random Forest and Support Vector Machines (SVM), also performed well, LGBM's ability to handle large volumes of data with speed and precision gave it a clear edge. Despite its strengths, LGBM's interpretability remains a challenge, but its outstanding performance in this study highlights its potential for real-world deployment. Ultimately, AI-driven detection methods like LGBM are critical for safeguarding online spaces and mitigating the risks posed by fake profiles.

Future Scope

- **Improved Model Interpretability**: Work towards developing models that offer greater interpretability and explainability of decision-making processes.
- **Real-Time Detection**: Enhance models for real-time fake profile detection to address emerging threats more effectively.
- **Cross-Platform Detection**: Extend the solution to handle other platforms like TikTok, LinkedIn, and Reddit for broader applicability.

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