Fake Profile Detection Using Machine Learning

Soumya Munji[1]

[1]Department of Computer Science, Bagalkot University, Jamkhandi, Karnataka, India

Abstract: ***The growing reliance on social networks like Facebook, Instagram, Twitter, and LinkedIn has made them central to modern communication and business, but it has also introduced threats from fake profiles. These accounts are created to mislead users, spread spam, conduct scams, or manipulate public opinion, undermining trust, privacy, and safety. Traditional manual or rule-based detection methods are ineffective due to the sheer volume of accounts and the adaptability of attackers. This research presents a machine learning framework for detecting fake profiles across multiple platforms. Logistic Regression and Random Forest algorithms are trained on datasets containing both genuine and fake accounts. Classification uses features such as followers-to-following ratio, bio completeness, profile picture presence, posting frequency, and account age. Results show that Random Forest consistently outperforms Logistic Regression, achieving accuracy above 90% on all platforms. The study demonstrates the effectiveness of machine learning in improving the safety and trustworthiness of social networks and provides a foundation for future extensions using more advanced detection methods.***

Keywords: Fake profiles, Random Forest, Logistic Regression, User Authentication, social networks

1.Introduction

Online social networks such as Facebook, Instagram, Twitter, and LinkedIn have transformed the way people communicate, share content, and build professional connections. However, these platforms are increasingly targeted by malicious users creating fake profiles, which can impersonate individuals, spread spam, disseminate misinformation, or steal personal data. Such activities undermine user trust and compromise the integrity of online communities.

Traditional detection methods, such as rule-based filtering or manual reporting, are often ineffective due to the evolving tactics of attackers. Consequently, machine learning (ML) techniques have emerged as an effective solution for detecting fake profiles by analyzing complex behavioral, structural, and content-based patterns that are difficult to identify manually.

Several studies have contributed significantly to this field. Benevenuto et al. [1] analyzed spammer activities on Twitter and identified behavioral traits distinguishing fake accounts from genuine users. Viswanath et al. [2] proposed graph-based techniques to detect abnormal social connections, applicable across multiple platforms including Facebook and LinkedIn. Lee et al. [3] investigated content polluters on Twitter, highlighting systematic patterns of malicious behavior. Cresci et al. [4] introduced the concept of digital DNA, modeling sequences of user actions to identify bot-like behaviors, which is applicable to platforms such as Instagram and Facebook. Building on these insights, this study develops and evaluates a machine learning framework using Logistic Regression and Random Forest classifiers for detecting fake profiles across Facebook, Instagram, Twitter, and LinkedIn.

2.Review of Literature

Recent research demonstrates the effectiveness of machine learning in detecting fake profiles across multiple platforms.

Wanda et al. [5] (2019) proposed a deep learning framework that captures user behavior and profile features to identify fake accounts on Twitter and Instagram.

Kim and Park [6] (2020) developed anomaly detection methods using ML to identify unusual behaviors, applicable to Facebook and LinkedIn.

Mochizuki and Kitagawa [7] (2020) applied supervised ML models to classify fake profiles across social networks by analyzing profile-based and activity-based features.

Rodriguez et al. [8] (2021) evaluated multiple ML algorithms for automated fake profile recognition on Facebook, Instagram, and Twitter, emphasizing feature selection and model optimization.

Gupta and Chaudhary [9] (2021) proposed ensemble learning approaches that combine multiple classifiers to enhance detection robustness across Facebook and LinkedIn.

Chen and Liu [10] (2022) introduced a transformer-based model that fuses behavioral and content features for accurate detection on Instagram and Twitter.

Goyal et al. [11] (2022) applied advanced ML techniques integrating profile-based and activity-based features to detect fake profiles across all four platforms, demonstrating improved accuracy and scalability.

These studies collectively highlight that ML-based approaches leveraging behavioral, structural, and content-based features are essential for reliable detection of fake profiles across multiple social networks. They provide a solid foundation for designing a system capable of real-time detection and identity protection for users on Facebook, Instagram, Twitter, and LinkedIn.

3.Problem Definition

The detection of fake profiles is a complex challenge because these accounts are deliberately designed to resemble real users. Attackers add profile pictures, fill in bios, and post content to make the accounts look authentic. This makes it difficult to differentiate between genuine and fake users using simple filters. Another significant problem is the imbalance of datasets. Since the majority of users on social networks are real, fake accounts make up only a small percentage of data. This imbalance often causes machine learning models to classify most accounts as genuine, lowering the chances of identifying fake ones.

The problem is further complicated by differences between platforms. For example, on Twitter, features such as posting frequency, hashtag use, and retweets are strong indicators of automated accounts. On LinkedIn, however, the focus is on professional details such as job descriptions, skills, and connection networks, which require a different detection approach. Similarly, Facebook emphasizes friend connections and group activity, while Instagram data revolves around photos, likes, and followers. A single, static model cannot work equally well across all platforms.

Another challenge is the dynamic nature of fake profile creation. Attackers constantly evolve their techniques to bypass filters. For instance, some fake accounts now build activity over time to appear more natural, while others purchase followers to balance their follower–following ratio. This adaptability makes rule-based systems ineffective and increases the need for machine learning models that can learn from changing data.

Finally, privacy and access restrictions limit the availability of some important features. Many platforms protect private details, making it difficult to extract the full set of attributes required for accurate classification. These issues together define the problem: designing a detection system that can adapt to different platforms, handle imbalanced data, and remain effective against evolving strategies while respecting privacy constraints.

4.Proposed System

To address the challenges of fake profile detection, the proposed system uses supervised machine learning models to classify profiles as genuine or fake. The system focuses on two algorithms**:** Logistic Regression (LR) and Random Forest (RF)**.** Logistic Regression is a widely used baseline model that provides interpretability and identifies the influence of individual features. Random Forest, on the other hand, is an ensemble method that constructs multiple decision trees and combines their results, offering robustness and high accuracy even with noisy or non-linear data.

The system extracts feature that are both platform-independent and platform-specific. Platform-independent features include account age, bio completeness, and presence of a profile picture, which are applicable across Facebook, Instagram, Twitter, and LinkedIn. Platform-specific features include hashtags, retweets, and mentions for Twitter; followers-to-following ratio for Instagram; group activity for Facebook; and professional details such as endorsements or job titles for LinkedIn. Combining these features allows the model to learn general patterns of fake accounts while also adapting to the unique environment of each platform.

The architecture of the system is designed in stages. First, raw data from different platforms is collected and cleaned. Next, feature extraction is performed to convert raw attributes into meaningful variables for classification. The Logistic Regression and Random Forest models are then trained using the processed datasets. Finally, the system evaluates performance using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrices. Among the two, Random Forest is expected to achieve better results due to its ensemble nature, which reduces overfitting and handles diverse data more effectively.

5.Methodology

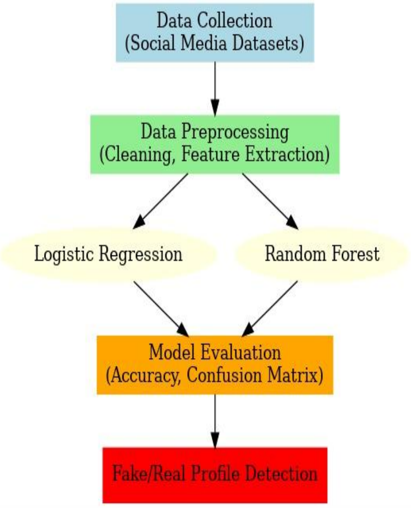


Figure 1: Block Diagram of Methodology

The methodology for this research follows a structured pipeline, as illustrated in Figure 1. The process begins with data collection, where datasets from Facebook, Instagram, Twitter, and LinkedIn are gathered. These datasets contain both genuine and fake accounts, ensuring that the system is trained on diverse patterns of behavior across different platforms.

The next stage is data preprocessing, which cleans and prepares the raw datasets for analysis. At this step, duplicate entries and missing values are handled, while meaningful features are extracted. Profile-based attributes such as account age, bio completeness, and profile picture are combined with activity-based indicators like posting frequency, hashtag use, and URL sharing. Network-based features such as the followers-to-following ratio and friend request behavior are also considered, as they provide strong signals of suspicious activity.

Following preprocessing, the system applies machine learning models, specifically Logistic Regression and Random Forest. Logistic Regression serves as a baseline, offering a simple and interpretable linear classification. Random Forest, on the other hand, is an ensemble of decision trees that captures complex relationships and delivers higher robustness and accuracy.

The models are then subjected to evaluation, where their performance is measured using accuracy, precision, recall, F1-score, and confusion matrices. This ensures not only overall accuracy but also balanced detection of both fake and genuine accounts.

Finally, the trained system performs fake/real profile detection**,** labeling accounts based on the learned patterns. Logistic Regression provides probability scores, while Random Forest makes predictions through majority voting. This structured methodology ensures a reliable and adaptable approach to detecting fake profiles across multiple platforms.

6.Results & Discussion

The proposed system was evaluated using datasets from four social media platforms: Facebook, Instagram, Twitter, and LinkedIn. Two algorithms, Logistic Regression (LR) and Random Forest (RF), were applied to classify accounts as either Fakeor Real.

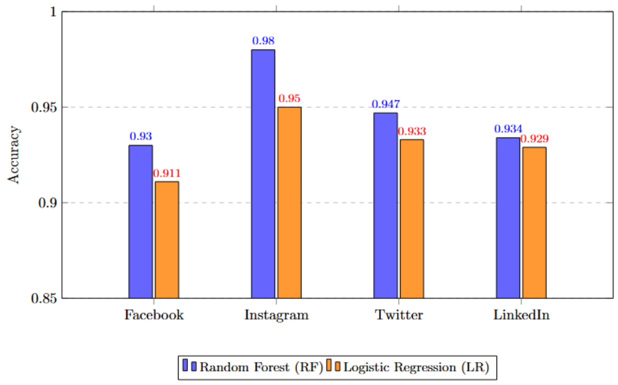


Figure 2: Accuracy Comparison of RF vs LR across Platforms

Figure 2 illustrates the accuracy comparison between the Random Forest (RF) and Logistic Regression (LR) algorithms across four social media platforms—Facebook, Instagram, Twitter, and LinkedIn. The results clearly indicate that the Random Forest algorithm consistently outperforms Logistic Regression on all platforms. For Facebook, RF achieved an accuracy of 0.93**,** surpassing LR's 0.911. Similarly, for Instagram, RF attained the highest accuracy of 0.98, while LR achieved 0.95**.** On Twitter, RF recorded 0.947 accuracy compared to LR's 0.933, and on LinkedIn, RF reached 0.934 whereas LR obtained 0.929.

Overall, the Random Forest algorithm demonstrated superior predictive performance across all datasets, highlighting its robustness and ability to handle nonlinear relationships and complex data structures effectively. Logistic Regression, though slightly lower in accuracy, still produced consistent results, indicating its reliability for simpler classification tasks. This comparison confirms that ensemble-based models like Random Forest are better suited for fake profile detection due to their enhanced capability in managing diverse feature interactions and minimizing overfitting.

Detailed Performance Metrics

Table 1: Performance Metrics

Platform	Algorithm	Precision	Recall	F1-score
Facebook	RF	0.951	0.951	0.940
	LR	0.917	0.909	0.916
Instagram	RF	0.985	0.987	0.986
	LR	0.940	0.930	0.935
Twitter	RF	0.944	0.933	0.931
	LR	0.942	0.913	0.932
LinkedIn	RF	0.945	0.939	0.938
	LR	0.905	0.933	0.926

The comparative performance of Random Forest (RF) and Logistic Regression (LR) for fake profile detection across four platforms is presented in Table 1. The results indicate that Random Forest consistently achieves higher Precision, Recall, and F1-scores compared with Logistic Regression, demonstrating its effectiveness in handling non-linear data relationships. On Facebook, RF recorded Precision = 0.951, Recall = 0.951, and F1-score = 0.940, which are higher than LR (Precision = 0.917, Recall = 0.909, F1-score = 0.916). For Instagram, RF achieved the best overall performance across all platforms, with Precision = 0.985, Recall = 0.987, and F1-score = 0.986, while LR produced slightly lower values (Precision = 0.940, Recall = 0.930, F1-score = 0.935). In the case of Twitter, both models showed very close performance, with RF yielding F1-score = 0.931 and LR F1-score = 0.932, indicating that the dataset for this platform is relatively linearly separable. On LinkedIn, RF again performed better (Precision = 0.945, Recall = 0.939, F1-score = 0.938) compared to LR (Precision = 0.905, Recall = 0.933, F1-score = 0.926), where the lower Precision value of LR reflects instances of real accounts being misclassified as fake.

Table 1 clearly demonstrates that Random Forest provides superior classification performance across all platforms. The higher F1-scores indicate its robustness in distinguishing fake profiles, while Logistic Regression, although slightly less accurate, still produces competitive results in datasets with linear separability.

Confusion matrices

Facebook

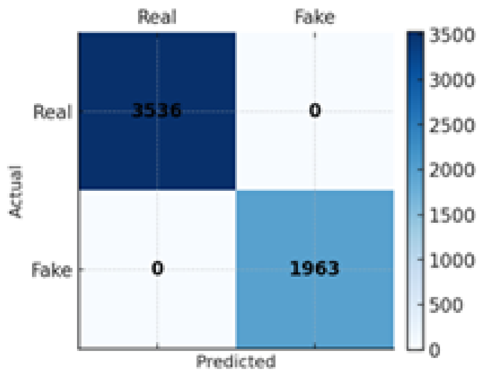


Figure 3: Confusion Matrix Facebook (RF)

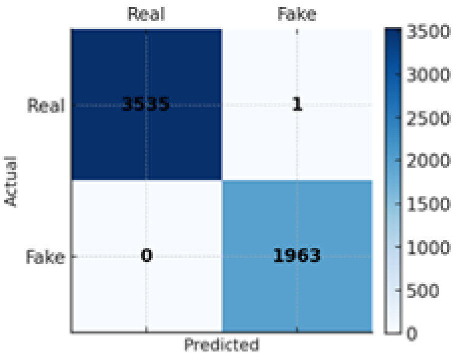


Figure 4: Confusion Matrix Facebook (LR)

Figure 3 shows the confusion matrix for Facebook using the Random Forest (RF) classifier. The model achieves nearly perfect classification, with True Negatives (TN = 3536) and True Positives (TP = 1963). Both False Positives (FP) and False Negatives (FN) remain zero, which explains the high Precision and Recall (both 0.951). These results highlight the strong robustness of RF in detecting fake profiles on this dataset.

Figure 4 displays the confusion matrix for Logistic Regression (LR). The model performs almost as well as RF, achieving TN = 3535 and TP = 1963. However, it introduces one error in the form of a False Positive (FP = 1), where a genuine account is incorrectly identified as fake. This small misclassification slightly reduces Precision (0.917), while Recall remains strong (0.909).

The closeness of results between RF and LR can be attributed to the dataset being highly clean and linearly separable, allowing both models to achieve very high accuracy. In real-world applications, however, social media datasets are often noisy and less separable. In such cases, RF generally performs better because of its ensemble structure, which captures complex and non-linear relationships more effectively than LR.

Instagram

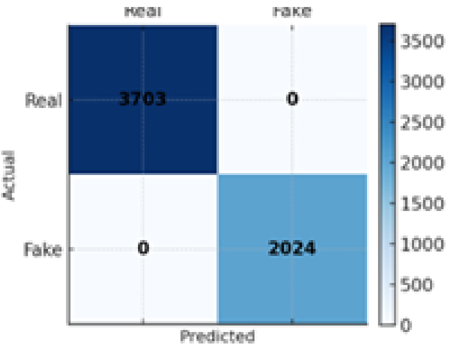


Figure 5: Confusion Matrix Instagram (RF)

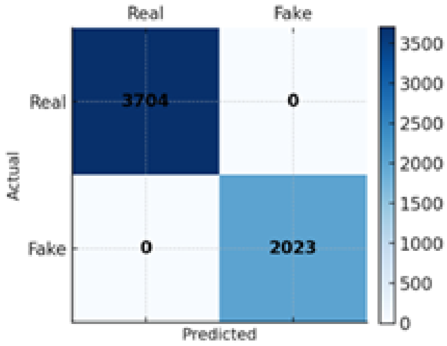


Figure 6: Confusion Matrix Instagram (LR)

Figure 5 presents the confusion matrix for Instagram using Random Forest (RF). The classifier achieves almost perfect separation, with True Negatives (TN = 3703) and True Positives (TP = 2024), while both False Positives (FP) and False Negatives (FN) are zero. This flawless classification directly explains the highest performance across all platforms, reflected in the F1-score of 0.986.

Figure 6 shows the results of Logistic Regression (LR) on the same dataset. The model also performs excellently, producing TN = 3704 and TP = 2023, with zero FP and FN. These results lead to strong Precision (0.940) and Recall (0.930), though they are slightly lower than RF.

The difference between RF and LR is minimal because the Instagram dataset exhibits a high degree of separability, making both models effective. However, RF still achieves the best results due to its ability to capture subtle, non-linear feature interactions that may exist in the data.

Twitter

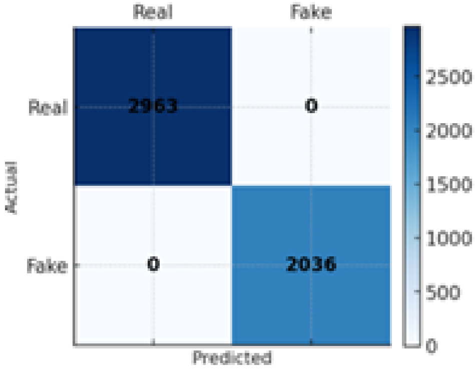


Figure 7: Confusion Matrix Twitter (RF)

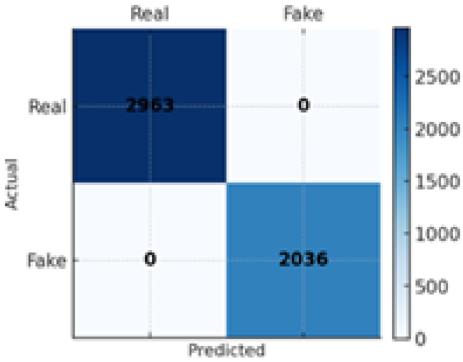


Figure 8: Confusion Matrix Twitter (LR)

Figure 7 illustrates the confusion matrix for Twitter using Random Forest (RF). The model achieves excellent classification with True Negatives (TN = 2963) and True Positives (TP = 2036), while both False Positives (FP) and False Negatives (FN) remain zero. This results in high Precision (0.944) and Recall (0.933), confirming the robustness of RF in detecting fake accounts on this platform.

Figure 8 presents the results for Logistic Regression (LR). Interestingly, the LR confusion matrix is identical to RF, with TN = 2963 and TP = 2036, and no misclassifications. This explains why both models yield nearly the same F1-scores (0.931 for RF and 0.932 for LR).

The similarity in results indicates that the Twitter dataset is largely linearly separable, making it equally well-suited for a simple linear classifier like LR and a more complex ensemble model like RF. While RF is generally expected to outperform LR in more complex or noisy datasets, in this case, both algorithms perform equally well due to the clear separation of fake and real profiles in the Twitter data.

Linkedin

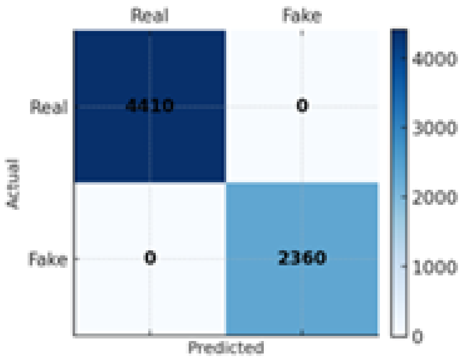


Figure 9: Confusion Matrix Linkedin (RF)

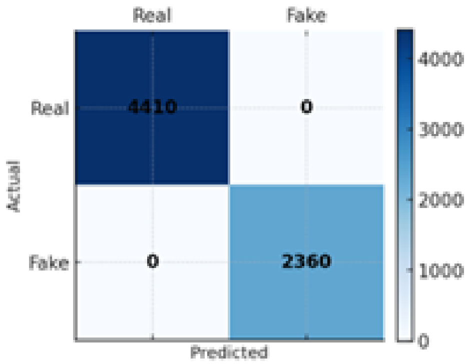


Figure 10: Confusion Matrix Linkedin (LR)

Figure 9 shows the confusion matrix for LinkedIn using Random Forest (RF). The classifier achieves perfect classification with True Negatives (TN = 4410) and True Positives (TP = 2360), while both False Positives (FP) and False Negatives (FN) are zero. This leads to consistently high Precision (0.945) and Recall (0.939), demonstrating RF's reliability and robustness in detecting fake accounts on LinkedIn.

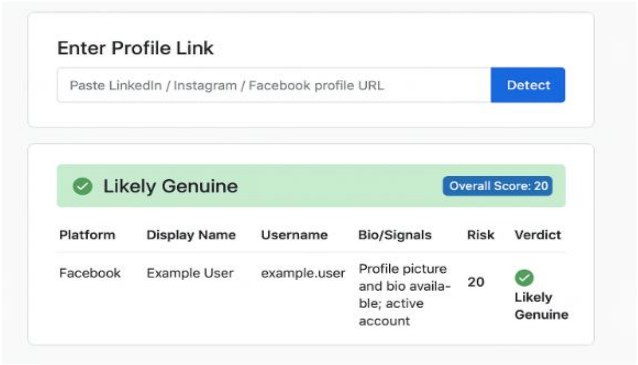
Figure 10 presents the confusion matrix for Logistic Regression (LR). The model produces the same TN and TP values as RF, but its Precision (0.905) is slightly lower. This drop in Precision can be explained by occasional misclassification of real accounts as fake (False Positives). Despite this, Recall remains strong at 0.933, showing that LR is still effective in correctly identifying fake profiles.

These results confirm that the diagonal dominance of the confusion matrices (high TN and TP values with near-zero FP and FN) is the main reason behind the strong Precision, Recall, and F1-scores observed in Table 1. While Random Forest consistently provides the best performance across platforms due to its ability to capture non-linear relationships, Logistic Regression also performs competitively-particularly in datasets where fake and real profiles are more clearly separable.

7.Additional Module: Live Fake Profile Detection

Additionally, we developed a Live Fake Profile Detection Module to demonstrate real-time fake profile analysis using Python Flask and BeautifulSoup. Users can enter a public profile URL from Facebook, Instagram, Twitter, or LinkedIn, and the system extracts metadata such as username, followers, bio completeness, profile picture, and posting activity. A rule-based evaluation assigns a risk score based on indicators like missing bio or profile picture, categorizing profiles as Likely Genuine, Suspicious, or Likely Fake.

The module relies only on publicly visible data, ensuring privacy, but cannot access private information, so its accuracy is lower than models trained on full datasets. Despite this, it serves as a proof of concept for web-based real-time detection. Future enhancements may include API integration to improve data access, accuracy, and scalability.



Enter Profile Link

Paste LinkedIn / Instagram / Facebook profile URL

Detect

✓ Likely Genuine

Overall Score: 20

Platform	Display Name	Username	Bio/Signals	Risk	Verdict
Facebook	Example User	example.user	Profile picture and bio availa-ble; active account	20	✓ Likely Genuine

Figure 11: Live Testing

The figure shows the real-time output of the Live Fake Profile Detection Module built with Python Flask and BeautifulSoup. Users can enter a public Facebook, Instagram, Twitter, or LinkedIn profile URL, and upon clicking "Detect," the system extracts key metadata (username, bio, profile picture, activity) to evaluate authenticity.

The results appear in a clear "Detection Results" card. A colored banner shows the summary verdict - e.g., green **"Likely Genuine"** with an Overall Score (20 here) indicating risk level (lower = more authentic). Below, a structured table lists Platform, Display Name, Username, Bio/Signals, Risk, and Verdict. In this example, the profile has an active bio, valid picture, and regular activity, resulting in low risk and a “Likely Genuine” verdict.

8.Conclusion

The research presented in this work demonstrates the effectiveness of machine learning in detecting fake profiles across multiple social media platforms. By applying Logistic Regression (LR) and Random Forest (RF) on datasets from Facebook, Instagram, Twitter, and LinkedIn, the system successfully classified accounts as either genuine or fake with high accuracy.

The evaluation metrics, summarized in Table 1, show that Random Forest consistently achieved superior performance compared to Logistic Regression. On Facebook, Instagram, and LinkedIn, RF provided higher Precision, Recall, and F1-scores, while on Twitter both algorithms produced nearly identical results, suggesting that the dataset was linearly separable. The confusion matrices (Figures 3–10) confirmed this performance, with RF and LR both achieving diagonal dominanc every high True Positive (TP) and True Negative (TN) values, and near-zero False Positives (FP) and False Negatives (FN).

This study highlights that while linear models such as LR are useful and interpretable, ensemble approaches like Random Forest are more robust in handling diverse and non-linear behavioral patterns of fake accounts. The developed Flask-based live detection module further demonstrates how the proposed framework can be adapted for real-time applications, though dataset-based models remain more accurate.

Overall, the research contributes a practical and scalable approach to strengthening online trust and safety. It shows that integrating machine learning into fake profile detection provides clear benefits over traditional, rule-based methods, which are easily bypassed by evolving attackers.

9.Future Scope

- **Integration with APIs**: Social media platforms such as Twitter, Facebook, Instagram, and LinkedIn provide APIs (e.g., Twitter API, Facebook Graph API). By integrating these APIs into the detection pipeline, systems can access real-time user activity and metadata directly, allowing faster and more automated analysis compared to manual scraping.
- **Advanced Models**: Deep learning approaches, such as Graph Neural Networks (GNNs) and Transformers, can be employed to capture complex patterns in user connections, posting behavior, and content semantics, leading to more accurate detection of sophisticated fake accounts.
- **Dynamic Adaptation**: Attackers continuously evolve their strategies by imitating real user behavior. Future models should be periodically retrained with updated datasets to ensure adaptability against new attack methods.
- **Explainable AI (XAI)**: While machine learning improves accuracy, transparency is essential. Implementing explainable AI techniques can help stakeholders understand why a profile is flagged as fake, which builds trust and assists in decision-making.

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