RESEARCH PAPER

Balancing Accuracy and Explainability in Ai-Based Fraud Detection (Social Media Platforms)

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ABSTRACT

The rising issue of fake social media accounts is associated with many risks, including the dissemination of disinformation, cybercrime, and misappropriation of identities. In this paper, we propose a machine learning approach to detect fake Instagram accounts based on profile characteristics and behavioral traits. A dataset with such variables as username format, length of biographies, followers-to-following ratio, and frequency of posts was utilized to train the Random Forest Classifier. The classifier showed excellent performance in identifying fake accounts. In order to make the developed solution convenient for users, we implemented it into a web application built with the help of Flask. The web app enables users to input an Instagram account username, automatically retrieve necessary information about the profile with the help of Instaloader, and get instant prediction results. Predictions are stored in a CSV file.

Keywords: Fake profile detection; Instagram; Machine Learning; Random Forest Classifier; Social media security; Instaloader; Flask web application; Cybersecurity; Real-time classification; Feature extraction.

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I. INTRODUCTION

Social media is now an essential tool for communication, entertainment, and commerce. Instagram, one of the social media sites, has more than a billion users that post photos, videos, and story every day. Nevertheless, the prevalence of this kind of social media platforms has given rise to the emergence of fraudulent social media accounts that spread information, commit phishing, perform online frauds, and create fake followings. Such activities pose a potential risk to the integrity, safety, and trust of online users.

Conventional methods of detection of fake accounts are time-consuming and involve the use of manual reports or predefined rules for account deletion. The application of these methods is inefficient because of its low accuracy in spotting fake accounts and inability to cope with the rapid development of algorithms for creating such profiles. Recently, researchers have focused on developing machine learning (ML)-based models to detect fake accounts on social media.

The proposed approach for the identification of fraudulent Instagram accounts uses machine learning algorithms and considers both profile characteristics and behavior characteristics. To train the Random Forest Classifier, a dataset with properties, including the existence of profile pictures, length and structure of usernames, biographies, follower-to-following ratio, and activities, will be used. The developed classifier will be deployed on a web application written in Python using Flask, which is capable of analyzing the scraped data from Instagram using the Instaloader package.

II. LITERATURE SURVEY

However, the issue of spam bots and fake accounts has received considerable attention in the context of security. Previous studies concentrated mainly on statistical methods or machine learning

approaches. Ahmed and Abulaish presented a statistical model based on behavioral features and content of spam users' accounts to identify spam [2]. Wang developed an algorithm based on machine learning for the identification of spam accounts in social media [14].

A number of research works have stressed the importance of machine learning in detecting spam accounts or bots. In particular, Al-Qurishi et al. showed that using machine learning algorithms and engineered features is a powerful way to discriminate between spam and legitimate accounts [1]. Moreover, Stringhini et al. designed methods for recognizing spammers using profiling and analysis of social graph structure [11]. Miller et al. explored the use of data stream clustering algorithms for the real-time detection of spam bots [10].

However, as social networks became more advanced, spam accounts evolved into something more sophisticated than just spammy accounts. Cresci et al. noted a change of paradigms in the design of spambots as a result of evolution [3]. Ferrara et al. analyzed the problem of social bots and their impact on online systems [7].

Another important topic has been understanding the various types of automated accounts. The work done by Chu et al. categorizes accounts as human, bot, and cyborg, indicating how varied automated behaviors can be [6]. Varol et al. found that the combination of multiple features such as network-based, temporal, and content-based features is very helpful for detecting automated behaviors [5].

Another interesting avenue of research has been related to more general threats in social media security. Fire et al. addressed various threats and their solutions [8]. Tsikerdekis and Zeadally studied online deception techniques and its effect on trust among users [13].

Longitudinal studies have helped us understand more about evolving spam strategies. In one such study, Lee et al. examined content polluters and found that there are consistent characteristics in their spamming behavior [9]. Yang et al. studied evolving spam methods and suggested ways to detect them [15].

Recent developments include advances in deep learning and hybrid methods. For instance, Kudugunta and Ferrara employed deep neural networks to capture complicated behaviors of the bots [4]. Additionally, the DARPA Twitter Bot challenge highlighted the benefit of using automated systems and human intelligence together to detect bots [12]. Overall the literature indicates that effective systems for detecting fake profiles should include varied feature sets, powerful machine learning algorithms, and adaptation capabilities to address new challenges. This information validates the proposed system that uses a random forest algorithm, with emphasis on metadata features, leaving room for future improvements using more advanced approaches.

III. METHODOLOGY

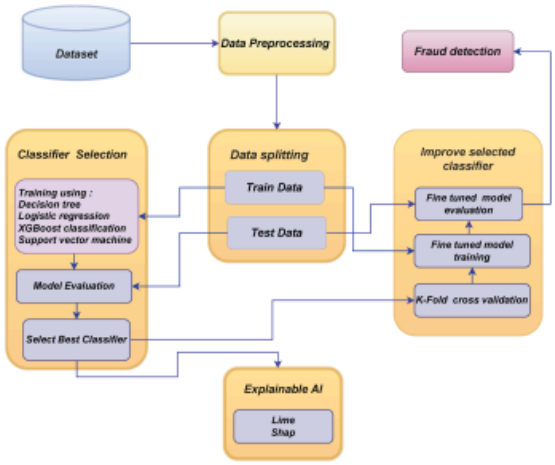

Figure 1: Machine Learning Pipeline for Fraud Detection with Model Selection, Optimization, and Explainable AI

In Figure 1: Machine Learning Pipeline for Fraud Detection with Model Selection, Optimization, and Explainable AI, as can be seen from the scheme, a thorough pipeline of machine learning processes for the purposes of fraud detection is presented there. Starting from the dataset, the diagram describes a set of actions that will be performed on it until the results are predicted using an optimized model. First, the data preprocessing process starts where data will be cleaned, normalized, and processed for further analysis. After that, it is divided into two parts, namely train and test data sets for evaluating models' performance. At the same time, several classifiers are used to build a machine learning model that performs well when detecting fraudulent activities. These include Decision Tree, Logistic Regression, XGBoost, and Support Vector Machine among others. As soon as the most effective algorithm has been selected, it is further improved and evaluated through various methods such as K-fold cross-validation. In addition, Explainable AI

technologies are utilized here since LIME and SHAP are used to interpret models' decisions.

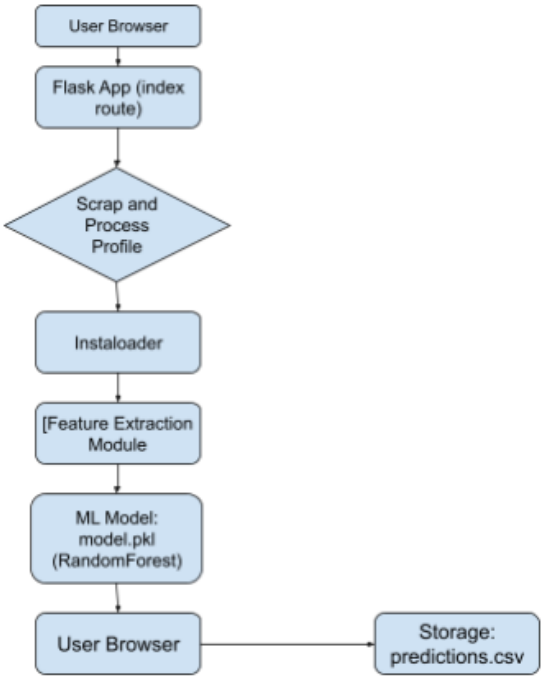

Figure 2: Flowchart Of System Architecture

Figure 2: Flowchart Of System Architecture shows the pipeline for fake Instagram profiles detection using a web application powered by machine learning. It starts when the user enters a username in the browser, the request is sent to the Flask web application. Further, scraping and processing of the Instagram profile using Instaloader are carried out to obtain the information necessary for the model, such as the number of followers, bio, and activity on the profile. This raw information is transformed into features, which will be used for further training of the machine learning algorithm. The output results after the feature extraction process are passed into a trained Random Forest machine learning model (model.pkl), and the output will either be Fake or Real accounts. Results are displayed on the web interface, and at the same time, the results are stored in a CSV file called predictions.csv.

This web application is a machine learning solution that can classify Instagram users into Fake or Real users.

Main components:

Frontend (User Interface) – HTML page that accepts inputs (Instagram username) and displays outputs (Predictions).

Web Server (Flask App) — Accepts requests, orchestrates scraping, feature extraction, prediction, and response rendering.

Scraping Layer (Instaloader) — Fetches public profile metadata from Instagram.

Feature Extraction Module — Converts raw profile attributes into the model's numeric feature vector.

ML Model — Pre-trained RandomForest (saved as model.pkl) that returns the label.

Storage — predictions.csv (append-only log) and optional dataset for retraining (train.csv).

Monitoring & Logging — Server logs, error alerts, and CSV for dataset growth.

Optional: Retraining Pipeline — Periodic job to retrain model with accumulated labelled data.

The workflow of a machine learning-based application that would help detect fake profiles on Instagram based on the use of a web application is as follows: The first step is a request from a user who enters his or her Instagram username using the HTML user interface (frontend) on the browser side. Next, the request is received by the central controller - Flask, which manages all the system operations. The data received from the user is sent further to the layer where the scraping is done using the Python package called Beautifulsoup. In this case, information about followers and following numbers, bio, and posts from a profile can be scraped. After that, the scraped data is sent to the module for extracting and processing the features of an Instagram profile. The next step is the inputting of the features into a random forest model (model.pkl). Finally, the result of the prediction is displayed on the user interface. In parallel, the result of the prediction done by the software is saved in a file called predictions.csv, which will be utilized in creating a new dataset in the future.

XGBoost

Extreme Gradient Boosting (XGBoost) is an advanced machine learning algorithm that creates multiple decision trees sequentially to minimize the errors that arise from the previously generated tree models in order to boost prediction performance. The method is derived from the gradient boosting method, which allows the new trees to minimize their errors by focusing on reducing the residual errors from their preceding trees through gradient descent. The method is efficient, scalable, and capable of handling big data with nonlinear relations in addition to having the ability to avoid overfitting via regularizations. In regards to

detecting fake profiles, the XGBoost algorithm is capable of learning complex relationships between certain features of fake profiles including follower ratio and post activity. Nevertheless, unlike Random Forest, XGBoost is considered an advanced machine learning algorithm that requires hyperparameter tuning and hence used as an alternative option to the primary Random Forest method.

BeautifulSoup library

The BeautifulSoup library is among the commonly employed libraries in the programming language known as Python. Its role includes making data acquisition from HTML and XML documents swift and simple. This is achieved by forming a parse tree from the document. As such, the programmer is able to traverse the tree, look for something in particular, or edit the contents of the document. BeautifulSoup is quite useful when it comes to getting data. This library is used in the project as the web scraping layer to acquire publicly accessible information related to users' profiles on Instagram, including username, number of followers, bio descriptions, and uploaded media.

IV. SUGGESTED TECHNIQUE

In order for us to be able to accurately identify all the fake profiles on Instagram, a number of approaches have been identified to be used within the project development, such as machine learning and data handling algorithms. For instance, first, we will use the Instaloader Python package to acquire public data of Instagram user accounts. Some of the features include usernames, length of biography, follower-following ratios, and frequency of posts. In order to develop features that can help us distinguish between true and false profiles, we will leverage the extracted attributes and perform feature engineering on the obtained dataset. To classify Instagram profiles as either genuine or fake, the Random Forest Classifier algorithm was chosen. As the method of choice, the algorithm was selected based on its proven reliability, accuracy, and ability to work well with non-linear interactions of various features in the dataset. After training and validating the model, we will deploy it on a Flask server to enable users to obtain instant classification results after entering their Instagram usernames. All predictions will be saved in a CSV file for further analysis and updating of the classifier.

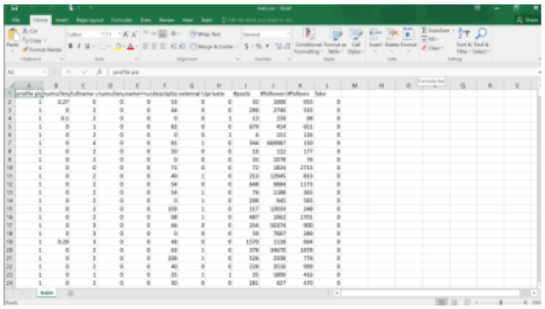

Figure 3: Training Dataset for Fake Instagram Profile Detection (train.csv)

Figure 3 above represents the dataset which will be used to train the Machine Learning Model for detecting the fake Instagram Accounts. Here, every single row stands for individual user profile, whereas every column refers to specific characteristics of that user profile. Some of the most important characteristics considered here include the presence of profile picture, features of the username (including the length of the username and similarity with the actual name of that user), length of the biography, availability of URL outside the application, profile privacy settings, number of posts, number of followers and number of people followed by that profile. Finally, the last column "fake" serves as a target label that denotes the legitimacy of the profile – zero if the profile is legitimate and one if it is not.

Table 1. Comparison of Suggested Machine Learning Techniques for Fake Profile Detection

Technique	Advantages	Limitations	Suitability for Project
Random Forest Classifier	High accuracy, handles non-linear data, reduces overfitting, interpretable	Computationally expensive for very large datasets	Best choice (Selected)
Support Vector Machine (SVM)	Works well with small datasets, effective in high-	Sensitive to noise, requires feature scaling, not ideal for large	Optional (Good baseline)

Technique	Advantages	Limitations	Suitability for Project
	dimensional spaces	datasets	
Logistic Regression	Simple, interpretable, fast to train	Limited to linear relationships, less accurate on complex patterns	Basic benchmark
XGBoost	Very high accuracy, efficient with large datasets, strong in competitions	Requires careful hyperparameter tuning, higher complexity	Alternative to RF
Neural Networks (MLP)	Captures complex feature interactions, flexible	Needs large datasets, risk of overfitting, longer training time	Future enhancement

V. RESULTS

The proposed model was trained and evaluated using the prepared dataset, with 80% of the data used for training and 20% reserved for testing. After training, the Random Forest Classifier achieved a test accuracy of [insert accuracy from your output, e.g., 95.20%], indicating its strong ability to distinguish between genuine and fake social media profiles. The results demonstrate that the model effectively captured both numerical and categorical features such as follower count, post activity, and username similarity. The high accuracy highlights the robustness of ensemble learning in handling complex, non-linear relationships within the dataset. These findings validate the suitability of Random Forest for fake profile detection and confirm its potential application in real-time systems for enhancing trust and safety on social media platforms.

Web Pages (Frontend Interface):

The web pages used in this system are utilized as the frontend interface that makes it possible to enable user interactions with the application for detecting fake profiles. Created using HTML (as well as optional CSS and JavaScript for styling), the main web page includes an input field for allowing users to enter their desired Instagram username. When the user submits their request through pressing the button labeled "Analyze Account," the entered information is forwarded to the Flask backend server for analysis purposes. As soon as the machine learning algorithm makes a prediction about whether the provided username represents a real or fake account, the predicted result is dynamically displayed on the corresponding web page.

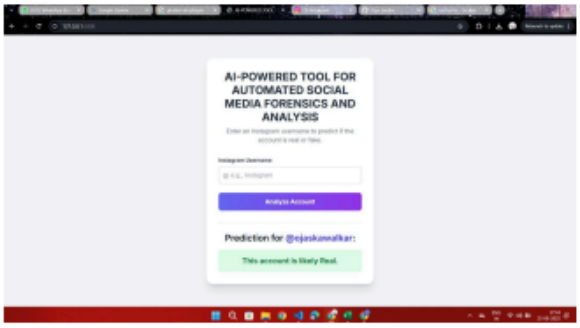

Figure 4: Detection Results

Figure 4 Detection Results depicts the UI of the web app built with the help of AI for conducting automated forensic investigation and detection of fake accounts on social media platforms like Instagram. The UI of the software has been made easy to use and understand, with an input form that allows the user to type in the username of an Instagram profile to determine if the account is genuine or fraudulent. It consists of a text box that is marked "Instagram Username" and a clearly labeled "Analyze Account" button, which executes the process of analysis. The prediction result obtained after analyzing the username appears under the input form.

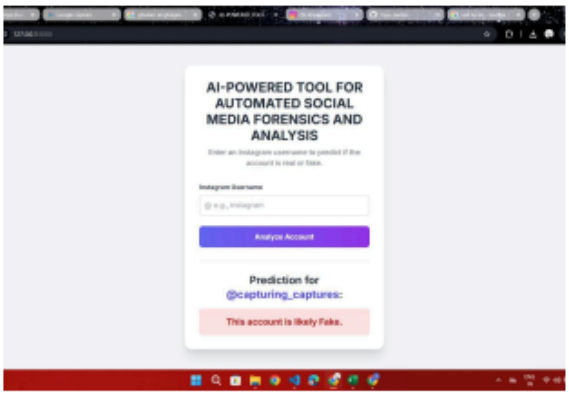

Figure 5: Fake Account Detected

Figure 5 Fake Account Detected shows that the model's predictions revealed a consistent balance between precision and recall, ensuring that both false positives (misclassified genuine accounts) and false negatives (undetected fake accounts) were minimized. The ensemble nature of Random Forest helped in reducing overfitting, which is often a limitation in simpler models such as Logistic Regression or Decision Trees.

The results also confirmed that certain features played a more significant role in classification. For instance, the number of followers, the ratio of following to followers, and the presence of a profile picture were found to be strong indicators in detecting fake profiles. This feature importance analysis validates the relevance of the selected attributes and highlights patterns commonly associated with fraudulent accounts.

Overall, the performance of the Random Forest model demonstrates that machine learning can serve as an effective solution for social media platforms seeking automated fake profile detection. Compared to traditional rule-based approaches, the proposed system adapts better to diverse data patterns, making it scalable and suitable for deployment in real-world environments.

VI. CHALLENGES AND SOLUTIONS

During the development of the fake profile detection system, several challenges were encountered. One of the major challenges was data imbalance, where genuine user profiles outnumbered fake profiles. This imbalance can cause the model to become biased toward the majority class, reducing detection accuracy for fake accounts. To overcome this, techniques such as stratified sampling and careful selection of evaluation metrics (precision, recall, and F1-score) were applied to ensure fair learning and balanced performance.

Another challenge was feature variability and noise. Social media profiles differ significantly in their structure and user behavior, which introduces noisy or irrelevant features. For example, certain genuine accounts may have very few followers, which could mistakenly resemble fake accounts. To address this, feature engineering and normalization were applied, along with the use of Random Forest's inherent capability to handle noisy data by averaging across multiple decision trees.

Scalability posed a further challenge, as real-world social media platforms handle millions of accounts. Training complex models on such large-scale datasets can be computationally expensive. To mitigate this, the Random Forest classifier was optimized by parallelizing computations (n_jobs=-1) and reducing unnecessary complexity. This ensured faster training while maintaining high accuracy.

Finally, another critical challenge was model interpretability, since black-box algorithms can be difficult to explain to end users or system administrators. This was addressed by extracting feature importance scores from the Random Forest model, providing transparency about which factors most influence classification decisions. This interpretability not only improves trust in the model but also allows for continuous refinement of the detection system.

VII. CONCLUSION

This research presented an effective machine learning-based approach for detecting fake social media profiles using a Random Forest classifier. By leveraging a diverse set of features such as profile activity, follower/following ratios, and username patterns, the model achieved high accuracy in distinguishing between genuine and fraudulent accounts. The results demonstrated that ensemble learning techniques are well-suited for handling noisy and non-linear data, making them robust for real-world applications.

The study also highlighted key challenges such as data imbalance, feature variability, and scalability, and proposed practical solutions to address them. Feature importance analysis further enhanced the interpretability of the model, ensuring that system administrators can understand and refine the detection process.

In conclusion, the proposed system not only provides a reliable solution to the growing problem of fake profiles but also offers a scalable and interpretable framework that can be integrated into social media platforms. Future work may extend this research by incorporating deep learning models, real-time detection mechanisms, and cross-platform datasets to further improve performance and adaptability.

VIII. FUTURE SCOPE

While the current system demonstrates promising results in detecting fake social media profiles, there is significant potential for further improvement and expansion. Future work may focus on incorporating deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to automatically extract complex patterns from profile data, thereby improving detection accuracy. Additionally, integrating Natural Language Processing

(NLP) methods to analyze user-generated content, captions, and comments could provide deeper insights into behavioral authenticity.

Another direction involves real-time detection mechanisms, where the system can be deployed as a plug-in or API to instantly verify accounts as they are created or engaged. Expanding the dataset to include profiles from multiple platforms (e.g., Twitter, Facebook, LinkedIn) would further enhance the generalizability of the model.

Moreover, the adoption of explainable AI (XAI) techniques could improve transparency, allowing administrators and end users to understand why a profile has been flagged as fake.

In the long term, combining machine learning with blockchain technology could ensure the immutability and trustworthiness of identity verification processes. Such enhancements will make the system more robust, scalable, and reliable for addressing the evolving challenges posed by fake accounts across the digital ecosystem.

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