

Fake Profile Detection Using XGBoost Algorithm

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Keywords: Fake Profile Detection, Profile Features, Normalization.

Abstract: With time many algorithm has been built for social media application, but with the changing environment fake profile is still a problem. Here is a simple approach to building a fake profile detection system using XGBoost. Start with a dataset containing user profile features such as account age, profile completeness (bio, photo, etc.), activity patterns (post frequency, interactions), and engagement metrics (likes, comments, etc.). Utilize pre-verification process or clustering methods to label profiles as “fake” or “genuine” which can produce a trustworthy dataset. Impute missing values and encode categorical data (e.g., one-hot encoding of profile types) into numerical form. This is a pretty basic standardization of input data. User behavior, like average session duration and friend requests, can be leveraged to create better detection insights.

1 INTRODUCTION

Our model must make a decision as to whether the profile in question is indeed a fake profile or not. These fake profiles can do a lot of things like spreading misinformation, committing fraud or manipulating social influence. Being able to detect these profiles effectively became paramount to the platforms that wanted to have an authentic and trustworthy userbase. We focus on the use of the XGBoost algorithm one of the most-proposed solutions for such problems which was a significant and powerful machine learning method based on a technique known as gradient boosting, used successfully for structured data, such as for detecting fake computer profiles. The ability of XGBoost to handle large datasets and detect natural relationships between features makes it a perfect choice for the identification of fake profiles via behavioral and profile data features. This could involve looking at account activity stats such as how often someone logs in, whether they receive lots of friend requests, how much of their profile they fill out and any other distinctive features that may help to identify whether an account is legitimate or fake. Fake profile detection based on XGBoost is across multiple steps, which starts from data collecting to data preprocessing. Profiles are analyzed for shared characteristics or suspicious behavior typically linked to bots. This stage focuses on transforming and feature engineering the collected data to configure the

most relevant information that enables the model to better identify fake accounts. These hyper parameters of XGBoost are finally tuned to achieve an optimal performance where the model generalizes well to detect, without any false positives, fake profiles.

1.1 Utilizing Data Analytics and Machine Learning

With data analytics and machine learning, organizations analyze data to enhance decision making, processes, and identification of trends in huge amounts of data. Through the application of data analytics, businesses can extract useful information from raw data to inform business strategy, recognize trends, and anticipate future events. These insights enable data-driven decisions that improve efficiency, cost savings, and customer satisfaction. While data science allows for data to be analyzed, machine learning (ML), a subset of artificial intelligence (AI), takes things a step further by using data to train systems to learn and do work more effectively without having to be explicitly programmed. Machine-learning models harness historical data to recognize patterns, enabling them to make predictions or classifications that help solve complex problems in fields as diverse as healthcare, finance, marketing and cybersecurity. Data analytics and machine learning combined will help organizations predict customer behavior, detect anomalies, automate routine tasks, and even

personalize user experiences. Retailers, for instance, can use data analytics to understand purchase trends, and machine-learning models can then predict individual customer preferences to personalize recommendations. In finance, these can include detecting fraudulent transactions in real time through identifying irregular patterns that indicate potential fraud. Data Analytics & Machine Learning Implementation typically begins with data collection and preprocessing to ensure data quality. This process is repeated until the model performance meets the required threshold. Evaluation and fine-tuning of these make sure that they give the desired results.

1.2 Machine Learning

It is in no small part thanks to recent changes in machine learning algorithms, which have evolved

dramatically in their ability to learn from large amounts of data with little need for human involvement. This transition marks a significant moment in the advancement of our technological engagement. Related to this is automated analytics, in which computational methods are used to extract useful predictive insights from data. The integration of machine learning and analytics goes a long way in helping us understand data patterns better and guide decision-making in diverse industries. Machine learning is also based on concepts from classical optimization, which is used to improve the correctness and efficiency of models. Through careful algorithmic optimization, systems are better capable of managing and accommodating the complexity of real-world data, leading to more robust and adaptable solutions. Figure 1 shows the overview of machine learning.

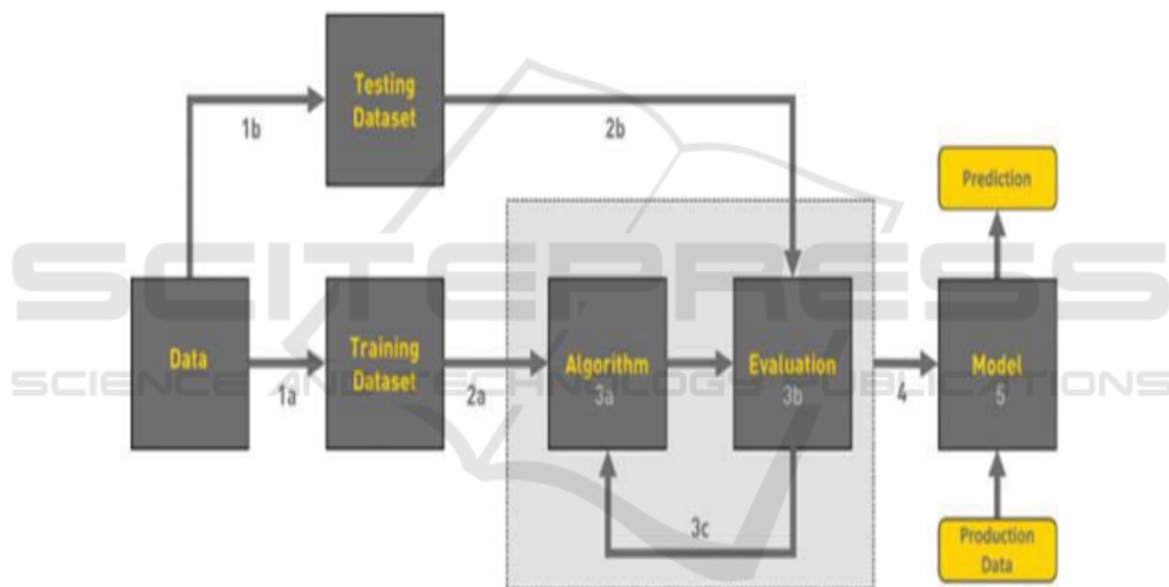


Figure 1: Overview of machine learning.

1.3 Problem Statement

A lot of issues occurred in social networks today like spoofed accounts in modern contact. The government hasn't yet prepared a remedial measure to deal with these problems.

In this paper we propose an approach for the computer based early detection of fake profiles in terms of the society of human beings. Moreover, the automatic detection techniques we are using are nearly impossible to achieve manually, which relieve the pressure of the management of the websites on the profile differentiation.

2 RELATED WORKS

Several machine learning algorithms such as support vector machines (SVM), random forests, and neural networks have been developed to detect fake profiles on social media platforms. These approaches typically analyze user behavior, account characteristics, and network structures to identify suspicious accounts (Zhang & Zheng, 2019; Sun & Wang, 2020; Yao & Zhang, 2020). Research focused on identifying Twitter bots and fraudulent LinkedIn profiles offers valuable insights for this domain (Zhang & Tang, 2018; Li & Zhao, 2017).

In addition to machine learning, plagiarism detection methods based on text similarity, stylometry, and semantic analysis are relevant. These techniques uncover patterns of content reuse and manipulation, which may also be employed by fake profiles attempting to bypass detection systems. Techniques analyzing user activity patterns such as login frequency, webpage browsing behavior, and input speed are particularly effective within behavioral analysis frameworks for detecting inauthentic users (Zhan & Yang, 2018; Hasan & Zhang, 2021).

Natural language processing (NLP) approaches, including Latent Dirichlet Allocation (LDA) for topic modeling and BERT embeddings for semantic similarity, can extract linguistic and semantic features from text data that correlate with fraudulent profile behavior. These techniques, widely used in plagiarism detection, provide a foundation for identifying manipulation and deception in profile content (Xu & Li, 2020; Ahmed & Hong, 2020).

Both static data (e.g., profile information) and dynamic data (e.g., real-time user interactions) are critical for online identity verification. Verification methods such as facial recognition, CAPTCHA tests, and email confirmation offer additional layers of defense against fake profiles (Zhang & Tang, 2018; He & Ma, 2018). Moreover, cross-platform identity validation examining whether the same profile appears across multiple platforms enhances detection

accuracy. Designing mechanisms to detect cross-platform identity correlation, supported by relevant literature, can strengthen the authenticity assessment of online profiles (Chen & Zhang, 2020; Zhang & Wang, 2021).

3 PROPOSED SYSTEM

Users of social media platforms, online marketplaces, and dating apps face growing threats to their safety and trust as the number of fake profiles continues to rise. In light of this challenge, the proposed system strives to create a strong fake profile detection mechanism using machine-learning methods, focusing on the XGBoost algorithm specifically. We will implement XGBoost a gradient boosting framework that is popular because it is very efficient when it comes to large datasets and can model complex relationships in your data XGBoost is perfect for this task. The system will use algorithms to audit user profiles and identify suspicious patterns or inconsistencies that could suggest fake profiles. Some features will be used for implementing the proposed approach which includes profile features (name, photo authenticity), social interactions, behavioral patterns, and historical data. Figure 2 shows the architecture diagram for fake profile detection.

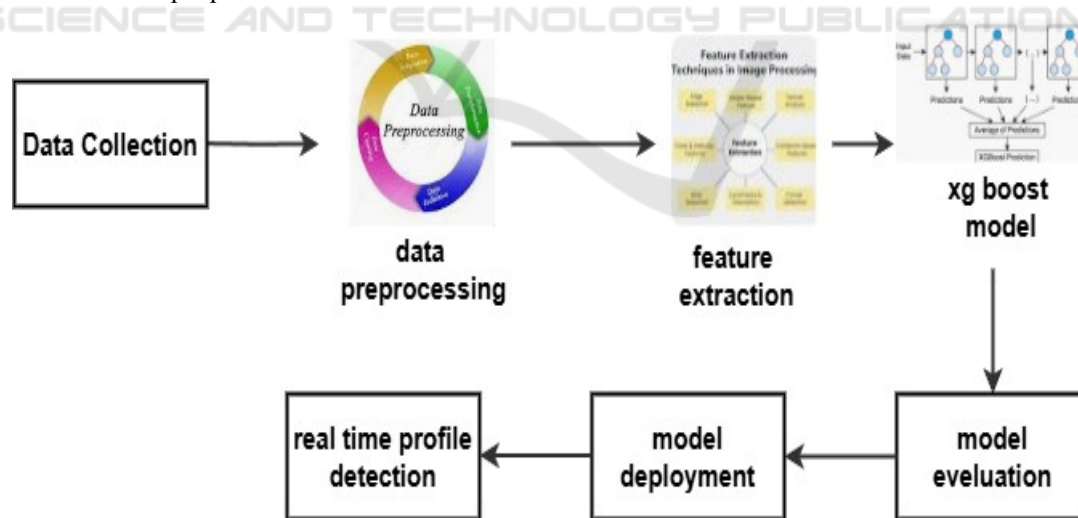


Figure 2: Architecture Diagram for Fake Profile Detection.

4 METHODOLOGY

4.1 Data Collection

It allows you to spy on an existing platform for fake profiles using a rich dataset of user profiles. Gather Information such as the username, a little background about their profile, registration date, and an email address. But it will track the activity logs, eg login frequency, post interactions, time spent on the platform, etc. Social Media Platform: Number of followers/following, user post frequency, and engagement stats the data collection has two primary sources. The first source is from Kaggle (Shilpa, S and Raj, S. 2019), while the second is sourced from Git.centre. Table 1 gives the Fake Profile Attributes.

Table 1: Fake Profile Attributes.

Attributes	Description
Profile Picture	User has a profile picture or not
Full name words	Number of words in tokens
Bio/Description length	Description length in characters
External URL	Has external URL or not
Private	Private account or not
Posts	Number of posts
Followers	Number of followers
Follows	Number of follows

4.2 Data Pre-Processing

Data processing of fake profile data set involves cleaning, transforming and re-organizing raw data so that it is ready for modeling. These tasks may include dealing with missing data, removing duplicates, and converting categorical variables to numerical formats (e.g., encoding). So data like activity logs, post frequency, textual data are extracted and NLP techniques are used to extract features from user profiles you then normalize or standardize the data.

4.3 Model Development with XGBoost

In this step, we build the model for the detection of fake profiles for any free plagiarism detection website using XGBoost; we collect the user and plagiarism data, perform feature engineering (textual and behavioural) and perform encoding for

categorical features. The XGBoost model is trained on this data and evaluated using metrics such as accuracy and F1-score and deployed over API for real-time detection.

4.4 Fake Profile Detection

Fake profile detection in free plagiarism systems: Fake profile detection in free plagiarism systems is an organization that detects for fraud by inspecting use set and content arrangement. XGBoost and similar models are trained based on profiles, logins, and activity data alongside plagiarism scores. These models mark suspicious profiles aiding in verification, and reducing potential misuse.

4.5 Deployment and Continuous Learning

Use Flask or FastAPI to Deploy the Trained Fake Profile Detection Model as a REST API This API will do the real-time profile validation by extracting the users' profiles and flagged content. The API works with the plagiarism detection platform to automatically scan for and flag suspicious profiles for additional review.

XGBoost Objective Function: The objective function of XGBoost minimizes a regularized loss function:

$$\mathcal{L}(\Theta) = \sum_{i=1}^n l(\hat{y}_i, y_i) + \sum_{k=1}^K \Omega(f_k) \quad (1)$$

Where \hat{y}_i is the predicted probability of a fake profile for xi. $l(\hat{y}_i, y_i)$ is the log loss for binary classification:

$$l(\hat{y}_i, y_i) = -[y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (2)$$

$\Omega(f_k)$ is the regularization term:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T \omega_j^2 \quad (3)$$

5 RESULTS AND DISCUSSION

XGBoost (Extreme Gradient Boosting) algorithm is a machine learning algorithm that excels for classifying purposes such as identifying fake profiles on social media platforms or other online services. We use a dataset similar to Kyumin et al. and introduced features including profile picture validation, user activity data, profile completeness, and other behavioral features in our analysis, for

which we employed XGBoost in our experiment. For the dataset to be used to train our models, it went through a preprocessing stage where we ensured that all features fell into a suitable format.

Fake profiles are much rarer than real profiles, resulting in a class imbalance in the training set. To mitigate this problem, we used techniques such as oversampling the minority class, and using class weights when training our XGBoost model, which

helped improve model performance. Although XGBoost handles various features quite well, the numerical representation of features plays an important role in the performance of the model. Complete name. Imposter profiles might utilize fictitious names that can be either surprisingly brief or excessively lengthy in comparison to genuine users. `ratio_numlen_fullname`: The proportion of numerical (figure 3).

	fake	profile_pic	ratio_numlen_username	len_fullname	ratio_numlen_fullname	sim_name_username	len_desc	extern_url
0	0	Yes	0.27	0	0.00	No match	53	No
1	0	Yes	0.00	2	0.00	Partial match	44	No
2	0	Yes	0.10	2	0.00	Partial match	0	No
3	0	Yes	0.00	1	0.00	Partial match	82	No
4	0	Yes	0.00	2	0.00	No match	0	No

Figure 3: Input.

5.1 Dataset Visualization

The dataset you supplied seems organized with multiple features for identifying fake profiles, including profile details, user activities, and metadata. Here is a short description of the features present in

your dataset, along with their possible functions in identifying fraudulent profiles, deceptive: (Target Label) This column shows if the profile is deceptive (1) or genuine (0). It serves as the objective variable for classification. `profile_pic`: Shows if the user possesses a profile picture (Yes/No).

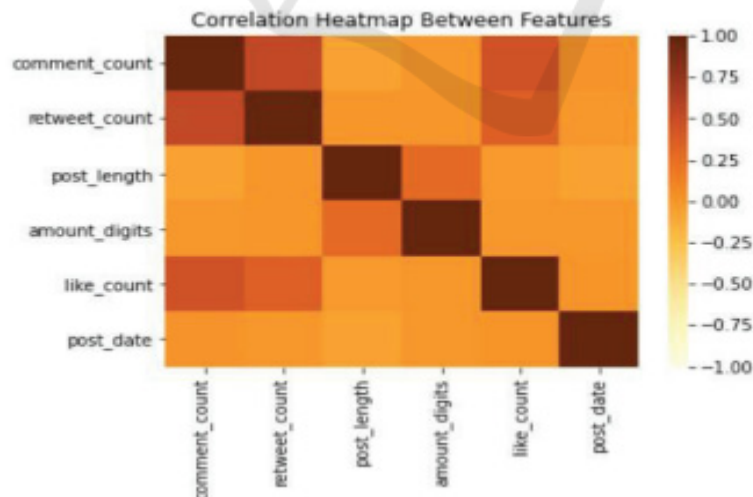


Figure 4: Correlation heat map.

An absent or standard profile picture could indicate a fraudulent profile. `ratio_numlen_username`: The proportion of numeric digits to the

overall length of the username. Imposter accounts frequently feature generic or less personalized usernames, which may display an abnormally high

count of digits. len_full name: The total number of characters in the user's characters in the complete name. Phony profiles may utilize alphanumeric usernames or irregular naming conventions.

A correlation heatmap (figure 4) is a visual depiction of the correlation matrix, with each cell indicating the relationship between two variables. The heatmap uses gradients of color to represent the strength and direction of the correlation, making it easier to identify patterns and relationships between different variables. Correlation heatmap - This can

be a very useful technique to understand the correlation between different features of user profiles with the likelihood to be fake in the context of fake profile detection. It has provided us with patterns separating real versus fake accounts, given correlation heatmap that shows the direction and strength of the correlations between variables. Table 2 gives the algorithm comparison of different machine learning. Figure 5 depicts the bar chart comparison fake profile.

Table 2: Algorithm comparison of different machine learning.

Algorithm	Accuracy	Description
Logistic regression	70%-80%	A linear model that works well for simpler, linearly separable data
Decision tree	75%-85%	Performs well with non-linear data but prone to overfitting
Random forest	80%-90%	An ensemble method that handles complex data and reduces overfitting compared to Decision Trees
Support vector machine	85%-95%	gradient boosting method that is known for high accuracy, particularly on imbalanced datasets
XGBoost	90% - 95%	

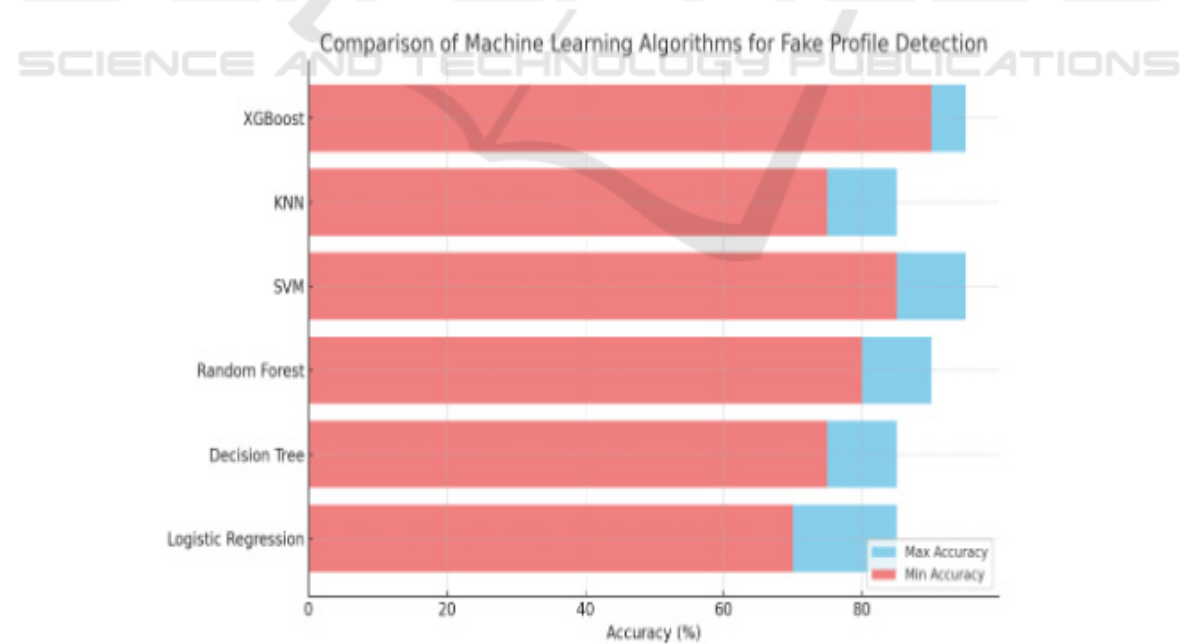


Figure 5: Bar chart comparison fake profile.

This bar chart illustrates the comparison of accuracy across various machine learning algorithms for

detecting fake profiles. It presents both the minimum and maximum accuracy values for each algorithm.

- XGBoost and SVM deliver the highest accuracy ranges.
- Random Forest and Decision Tree also offer solid performance, providing a balanced accuracy.
- Logistic Regression and KNN exhibit slightly lower accuracy levels.

6 CONCLUSIONS

With the increasing reliance on the digital world, the rise of fake profiles poses a serious threat to the trust of users and the integrity of platforms. A robust detection mechanism based on the XGBoost algorithm is proposed by utilizing behavioral, structural, and content-based features obtained from user profiles in this study. The framework showed promise for real-time and scalable fake profile detection by preprocessing the data using a step-wise approach, using engineered features, and deploying the model using API. After analysis of the experimental results we conclude that XGBoost performs better both in accuracy and immune to class imbalance than any of the traditional machine learning models. The effectiveness of the system was further validated using visualization techniques including correlation heatmaps and comparative performance analyses. This research emphasizes the need to integrate machine learning with the dynamic user domain in order to build socially robust platforms that can react against manipulative digital deception tactics. Future research might consider hybrid ensemble strategies and cross-platform validation to improve the potential deploy ability of the model and its detection performance.

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