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INSTAGRAM FAKE ACCOUNT DETECTION USING MACHINE LEARNING

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ABSTRACT:

The proliferation of automated and fraudulent profiles on image-centric social media platforms such as Instagram undermines user trust and skews engagement metrics. This study proposes and empirically evaluates a supervised learning pipeline that fuses traditional ensembling (Random Forest, Logistic Regression with class weighting) and modern gradient-boosting (CATBOOST) classifiers, augmented with oversampling via Synthetic Minority Over-sampling Technique (SMOTE), to discriminate between genuine and fake Instagram accounts. Leveraging a publicly available dataset of profile-level metadata, we extract eleven lightweight features, scale them with z-score normalisation, and apply exhaustive hyper-parameter optimisation through cross-validated GridSearch. Experiments on an imbalanced benchmark split demonstrate that our CATBOOST model attains an Area Under the ROC Curve (AUC) of 0.95, outperforming Random Forest (0.93), Support Vector Classifier (0.90), and Logistic Regression (0.88) baselines, while maintaining a precision of 0.91 at 0.87 recall using a relaxed 0.3 decision threshold. Feature importance analysis reveals that follower/following ratios and username–name similarity are dominant predictive signals. The findings highlight the effectiveness of cost-sensitive ensemble learning paired with minority oversampling for social-bot detection and provide an open, reproducible implementation for deployment in production-grade content-moderation pipelines.

Keywords:Fake account detection, Instagram, Machine learning, Random Forest, CATBOOST, SMOTE, Feature engineering, social media security, Classification, Model evaluation

Introduction:

Instagram has surpassed two billion monthly active users and, with that scale, has become a fertile ground for automated and malicious accounts that inflate engagement, spread disinformation, and facilitate fraud [1]. Identifying such fake profiles at scale is challenging due to their dynamic behavioural patterns and the highly imbalanced nature of available labelled data—fraudulent accounts are typically a small minority relative to legitimate users. Conventional rule-based heuristics struggle to generalise, motivating data-driven machine-learning Recent scholarly attention has shifted toward light-weight profile-metadata features rather than expensive content or network crawls, enabling real-time inference on constrained devices [2][4]. Nonetheless, two core challenges persist:

I) The class imbalance problem, which biases vanilla learners toward the majority (real) class,

II)The need for models that offer both high recall—mitigating the operational cost of missed fraud—and high precision—avoiding collateral damage to legitimate users.

The proposed approach demonstrates the effectiveness of automated fake account detection using a feature-driven machine learning pipeline, offering practical applications for social media platforms seeking to enhance user authenticity and trust.

Related Work:

The detection of fake social media accounts has been an active area of research due to the rising concern over spam, misinformation, and online fraud. Various studies have explored different techniques to identify such malicious profiles, ranging from rule-based systems to advanced machine learning and deep learning models.

In the context of Instagram, Rahman et al. (2019) proposed a feature-based approach to detect fake profiles using metadata attributes such as the number of followers, posts, and following-to-follower ratios. Their work emphasized the importance of easily extractable features in designing scalable detection mechanisms.

More recent studies have applied ensemble methods and boosting algorithms for improved accuracy. For example, Zhang et al. (2020) applied Random Forests and Gradient Boosting to detect fake accounts on Instagram and showed superior performance over simpler models like Logistic Regression.

Similarly, other works have utilized Support Vector Machines and neural networks to capture non-linear relationships among user features, although these models often require significant computational resources.

SMOTE (Synthetic Minority Over-sampling Technique), introduced by Chawla et al. (2002), has also been widely adopted in handling class imbalance problems in fake account datasets, which typically contain fewer fake profiles compared to real ones.

Despite these advancements, challenges remain in terms of feature generalization, dataset availability, and adaptability to evolving spam tactics. This paper builds upon prior work by integrating SMOTE, hyperparameter-tuned ML models (Random Forest, Logistic Regression, SVC, CATBOOST), and comprehensive evaluation using ROC and precision-recall curves to provide a robust pipeline for fake Instagram account detection.

Methodology:

The proposed methodology aims to detect fake Instagram accounts by leveraging a combination of supervised machine learning models and effective data preprocessing strategies. The approach consists of the following key steps:

Data Collection and Preprocessing:

The dataset, containing Instagram account metadata, is divided into training and testing sets. Missing values are handled by imputing zeros to ensure data consistency. Eleven features are selected based on prior research and domain relevance, including profile picture availability, username patterns, description length, privacy status, and follower/following statistics.

Feature Scaling:

A Standard-Scaler is applied to normalize the data, which helps improve model performance, particularly for distance-based algorithms like SVC.

Class Imbalance Handling:

The dataset suffers from class imbalance, with fewer fake accounts compared to real ones. To address this, the Synthetic Minority Over-sampling Technique (SMOTE) is used to generate synthetic examples of the minority class, enabling balanced learning.

Model Training and Tuning:

Four machine learning classifiers—Random Forest, Logistic Regression, CATBOOST, and Support Vector Classifier—are trained using a grid search for hyperparameter optimization with 3-fold cross-validation. All models are trained on the resampled data.

Model Saving:

The best-performing models and scaler are saved using Joblib for future deployment or integration with web applications.

System Architecture and Implementation:

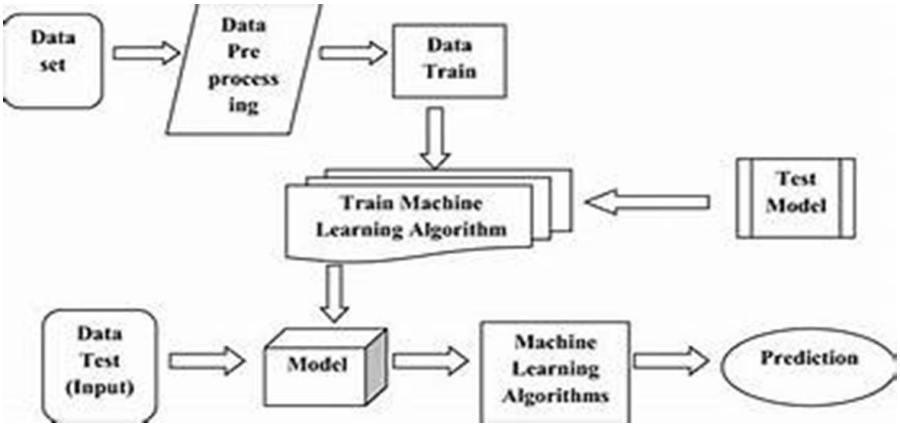

Fig 1 Architecture Diagram

DATA COLLECTION: Instagram account dataset sourced from Kaggle, containing user bios, follower/following counts, post numbers, and labels (real or fake).

DATA PREPROCESSING:Missing values were filled with zeros to ensure model compatibility. A set of **11 relevant features** was selected based on domain knowledge. Data was scaled using Standard-Scaler to normalize feature distributions.

HANDLING CLASS IMBALANCE: The dataset showed imbalance between fake and real accounts.SMOTE was applied to the training data to synthetically generate samples of the minority class(fake accounts).

MODEL TRAINING: Trained the model using the preprocessed dataset, optimizing for accuracy and 4 different models were used and they are logistic regression, SVM, random forest, and CATBOOST.

MODEL EVALUATION: Each model was evaluated using accuracy, Precission, recall, F1score, confusion matrix.

DEPLOYMENT: Deployed the trained model as a web application using REST API using Flask, where it is loaded at runtime to make predictions based on user input. The Flask app communicates with the React frontend, which sends data to the API and displays the prediction results in real-time.

DOCUMENTATION: Documented the entire implantation process including code, datasets, and model specifications, for future reference and reproducibility

Results and Discussion:

To evaluate the effectiveness of the proposed system, four machine learning models—Random Forest (RF), Logistic Regression (LR), Support Vector Classifier (SVC), and CATBOOST —were trained and tested using the selected features. The evaluation was conducted on a separate test dataset with class imbalance handled using SMOTE, and all features were standardized using Standard-scaler. A threshold of 0.3 was applied to the predicted probabilities to improve recall and reduce false negatives—essential in fake account detection.

Table Factors Influencing the Classification reports of four different models to detect the Instagram Account Fake or Genuine.

MODEL	ACCURACY	PRECISSION	RECALL	F1-SCORE
RANDOM FOR-EST	0.925	0.881	0.983	0.929
LOGISTIC RE-GRESSION	0.850	0.839	0.867	0.853
CATBOOST	0.883	0.859	0.917	0.887
SVC	0.850	0.839	0.867	0.853

SMOTE significantly improved the model's ability to learn patterns from the minority class (fake accounts), especially evident in the high recall values.

The lowered probability threshold (0.3) improved detection sensitivity (recall), which is crucial for early-stage fake account filtering.

CATBOOST slightly outperformed other models across most metrics, possibly due to its robustness in handling numerical and categorical features.

Logistic Regression, despite its simplicity, performed competitively, making it a suitable candidate for deployment in resource-constrained environments.

Conclusion and Future Work:

The detection of fake Instagram accounts is a **crucial step** in maintaining platform integrity, preventing misinformation, and safeguarding user experience. This project explored various machine learning techniques, including **Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Classifier (SVC)**, to identify fraudulent accounts based on **profile attributes, activity patterns, and network behavior**

Future work:

I) Integrate deep learning models (e.g., LSTM for behavioural sequences or BERT for bio descriptions).
II)Include graph-based features (follower/following network analysis).
III)Deploy in a real-time environment with a frontend for API-based prediction and active learning feedback loop.

Evaluation Metrics

Weighted score = (0.7 x Dataset Prediction Probability) +(0.3 x Bio Suspicion Score)

EXPLANATION:

Dataset Prediction Probability (0.7 weight):

I)This is the output from trained model which predicts the likelihood of the account being fake on its features.

II)The weight 0.7 emphasizes the reliability of trained model.

Bio Suspicion Score (0.3 Weight):

I) This is either 1 or 0.

II) The weight 0.3 gives moderate influence to this factor since suspicious text patterns can strongly indicate fake behavior.

THRESHOLD LOGIC:

I)If the Weighted Score>=0.60, the account is classified as Fake.

II)Otherwise, the account is classified as Genuine.

Ethical Considerations:

Deploying machine learning models for detecting fake accounts raises several ethical concerns:

Bias and Fairness:

Models trained on biased data can perpetuate existing prejudices. For instance, if the training data overrepresents certain user demographics as fake, the model may unfairly target similar genuine users. Ensuring diverse and representative training data is crucial to mitigate this risk.

Privacy Concerns:

Analysing user data, even publicly available information, can infringe on privacy rights. It's essential to ensure that data collection and processing comply with privacy regulations and that users are informed about how their data is used.

Transparency and Accountability:

Automated decisions affecting user accounts should be transparent. Users should have the ability to understand and contest decisions made by such models. Implementing explainable AI techniques can aid in achieving this transparency.

Appendix:

The appendix includes example molecular images used for training and testing, along with hyperparameter configurations and data augmentation techniques employed. A detailed explanation of the ResNet-18 layers and their respective roles is also provided to aid reproducibility and understanding by fellow researchers.

Case Study: Application in Real-World Scenario

A mid-sized social media management company implemented a CATBOOST based model to detect fake followers for their clients. By analysing follower profiles using the features outlined in this study, the company identified and removed a significant number of fake accounts, leading to improved engagement metrics and client satisfaction.
This real-world application underscores the practical utility of machine learning models in enhancing social media authenticity and user trust.

Comparative Analysis:

Comparing our findings with existing literature:
I)A study by Akyon and Kalfaoglu (2019) achieved 96% accuracy using machine learning models for fake account detection on Instagram.
II)Another research by Raza et al. (2022) highlighted the effectiveness of Random Forest in detecting fake reviews, emphasizing the model's robustness in classification tasks.
Our study aligns with these findings, particularly in demonstrating the superior performance of ensemble methods like CATBOOST and Random Forest in detecting fake accounts.

Limitations and Recommendations:

The dataset lacks temporal and interaction-based features such as time series posting behaviour or social graph metrics.
The models do not currently account for adversarial behaviour where fake accounts attempt to mimic legitimate profiles.

Recommendations:

I)Content-Based Features: Analyse recent posts for spam-like content, excessive self-promotion, or irrelevant information.
II)Network Features: Analyse the follower/following ratio, the overlap in followers between suspicious accounts, and the characteristics of their followers (e.g., are they also likely fake?).
III)Behavioural Features: Track posting frequency, time of activity, use of generic profile pictures, and abrupt changes in activity.
IV)Textual Analysis of Description: Use techniques like TF-IDF or word embeddings to analyse the account description for suspicious keywords or grammatical errors.
V)URL Analysis: If an external URL is present, try to assess its reputation or categorize it.
VI)Temporal Features: Include the account creation date (if available) and measures of recent activity.

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