



Fake Account Detection On Instagram Using Machine Learning

Karri Divya¹, Lanka Lokesh², Killada Vasudevarao³, Pitta Maruthi Reddy⁴, A.Venkateswara rao⁵

^{1,2,3,4}B. Tech Students, Department of Computer Science & Engineering – Data Science

Dadi Institute of Engineering and Technology, NH-16, Anakapalle,

Visakhapatnam-531002, AP

⁵Head of the Department, Department of Computer Science & Engineering – Data Science

Dadi Institute of Engineering and Technology, NH-16, Anakapalle,

Visakhapatnam-531002, AP

Abstract: Fake account detection on Instagram Fake account detection on Instagram Now, most systems use machine learning based on features, such as activity, profile data and interaction, to classify accounts into genuine or fake ones. Different models like Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine (SVM), and Neural Network have been used on this dataset and shown varying levels of performance with Random Forest achieving the best accuracy. These models do not scale well and struggle with complex large datasets. To overcome these limitations, we propose a fully-automated approach for detecting fake accounts based on a Deep Neural Network (DNN). The effective detection of fake accounts is further enhanced by the capability of DNNs consisting of multiple layers to automatically learn complex patterns from large amounts of data. Such a structured method significantly increases detection capabilities, where designs built for ALT to use traditional models yield poor results, with the foundation of better performance, real-time detection, and improved efficiency.

Keywords: Fake Account Detection, Instagram, Deep Neural Network, Machine Learning, Scalability, Social Media Security

INTRODUCTION

Instagram: The most popular social media platform in the world that has a paradigm shift in communications between us and influence on us in any ways. But with the growth of those platforms has also come an explosion in counterfeit accounts — a threat in its own right, let alone a major challenge in security, privacy and user experience. Criminal: Accounts can be used to spam, impersonate a person or brand, spread misinformation, scam businesses, and so on. Such accounts are toxic to the well, eroding genuine engagement and trust among users.

This is why we are identifying Fake Accounts and disabling them to maintain safety, transparency and trust in the Instagram community for the people. Old-fashioned methods of account-verification are low-throughput approaches that rely on manual reporting and flagging, to say nothing of the fact that with large data sets, the most significant examples can become lost in swamps of irrelevant activity. Here, Machine

learning(ML) techniques are powerful methods for automating the tasks of detecting known fake account. These techniques help to analyze logs about user profiles and user activities over time. We can also use things like whether or not someone is posting frequently, how often they are posting a particular type of content, whether or not they have followers and how they interact with them to help us determine if the account is real or fake.

Different types of folk machine learning algorithms have been used for this — Logistic regression, Naïve Bayes, Random Forest, SVM, and Neural Networks. OpenAI released a version of ChatGPT in December based on the text-generating GPT-3. The 5 Turbo model is essentially a more powerful version of ChatGPT models [1] and it works like butter on a single GPU machine. Text present in this project will use algorithm which is Account facking detection leaning algorithms which is based on Deep Neural Networks (DNNs) in order to overcome such problems. So ML is also pattern based but applied on continuous unit-scale level but deep neural network could be learn on large-scale data literacy with great accuracy in complex patterns. This will leverage state of the art in DNNs to further automate fake account detection, and eventually automate integrity on Instagram to render tightly-coupled rule based methods ineffective, inefficient and unreliable

LITERATURE REVIEW

This was a new area of research that focused on how fake accounts can be created and used on platforms like the social web such as Instagram which had fake accounts for spam going, fraud, impersonation, disinformation etc. There are several techniques in machine learning which have addressed this issue, with their own pros and cons. In this literature review, we present the key methodologies and research that have been developed for fake account identification systems.

Conventional ML Models to Detect Fake audio Both studies used traditional machine learning models in their early research using fake account detection. Most of these are derived from hand crafted features on things like account metadata, user behaviour trends, interaction statistics etc.

Logistic Regression and Naïve Bayes: According to the same reasoning, since we based our classification in simple probabilistic relations between feature and labels (real or fake), so we used such models to classify the accounts. But they are not so effective in the case of big or high dimensional data set and they much rely on linear methods which might not well represent user activities. Liu et al. focused on spam detection with applied Naïve Bayes and concluded with that the accuracy was moderate and effectiveness of the technique to predict the spam accounts on Twitter was moderate but not effective enough with high error-rates due to the limitations with accuracy and sensitive with the newer strategies of fraud.

Decision Trees & Random Forest: Random Forest classifiers are a group of decision trees running in parallel that has proven to be highly accurate in identifying opium accounts. Subramanian et al. However, reached an accuracy of only 73% for Logistic Regression within the realm of detecting fake accounts in social networks (2020) with Random Forest. Sure, h ise models (XGBoosts,etc.), also perform extremely well, but as you think of scaling up with just large datasets, there it poses its own set of challenges, also over here trying to encapsulate all these complex Schemas to make it to fetch wouldn't be possible.

Support Vector Machines (SVM) : SVMs have also been applied in recognizing activity using its property of classifying the data into distinct classes using hyperplanes. Chen et al. (2019) trained Support Vector Machine (SVM) on Instagram data achieving excellent true positives ratio out of the total positives, greatly exceeding naive models such as Naïve Bayes. But support vector machine, so when that surface is very large, it could be computationally expensive.

Fake Account Detection Using Deep Learning Techniques

To overcome these issues, scientists have begun employing deeper Learning methods since these methods are effective with high dimensional data. A DNN is a global algorithm used in deep learning models and has the ability to learn automatic hierarchical representations that can "learn to see" a relatively large volume of data that theoretically should provide a significant gain and advantages over traditional algorithms on high-dimensional and non-linear data.

Convolutional Neural Networks (CNNs): CNNs are typically decades for image processing projects, feature extraction; typically apply to social media sites like Instagram; model has fitted as a visual component (images, videos) in their resource to retain an important role in user behaviour. Singh et al. (Rafael and Čas 2021) used fake account detection based on just profile images using CNNs and it gave fair results in differentiating between fake accounts according to stock images or from other sources.

LSTMs and RNNs — RNNs and Long Short-Term Memory networks (LSTMs) were built to operate on sequential data and have been used to monitor user activity over a period of time. Zhang et al. Mohammadi et al. also utilized LSTMs. (2020), to model and predict users' behaviour patterns and user interaction styles on the Instagram platform (i.e., what a user posts and the frequency of posts over time, as well as how a user would potentially interact with other users including the types of users). Temporal information often relies on user activity, and these models excelled at detecting fake accounts and outperformed current state-of-the-art methods based on classical approaches.

DNN based approaches: The number of neural based models which deals with detecting fraudulent accounts such as DNN models been a very interesting trend as DNNs now a days have the potential of capturing such complex patterns states even for high volume of data. Li et al. Cao et al. (2022) deployed DNNs over a combination of user profile features, activity logs, and engagement metrics to identify Instagram fakes. Their model significantly outperformed traditional machine learning techniques in identifying professional fake accounts that use evasive techniques to avoid detection. DNNs contain more than two layers which help to extract the non-linear relations and gain deeper behaviour of accounts during detection.

Notta Botty, a distribution of Bots for each account

Feature Engineering: The Art of Getting the Best Features For this model Feature Engineering is the key to success of any model and making the feature engineering should focus on many factors like the season of these toys with those been produced because someperiod everything day those toys in particular relatively high high interest rate those can become a model in focus to add a tool of maximum use your effort to get the best for your efforts in the survey, in particular, the line of effort maximum effort give you a lot on the line where you create out of running your day to give a lot of food for thought you. Prior works examined several features such as account meta-data (e.g., profile data), behavioral (e.g., posting frequency, follower interactions) or content based features (e.g., hashtags, captions, images).

User Behaviour Features: Some metrics define user activity levels, user engagement rates, user interaction with its own followers etc (Gao et al. How do social bots transmog online information from social networks? (2019) published a collaborative Twitter bot on how much do fake accounts differ from human accounts in terms of frequency of posting, the ratio of followers to number of people followed, and the quality of comments. Fake accounts also post in unusual or botlike ways — that is, at an extremely high rate or with a very large ratio of followers to accounts followed.

Content Analysis Features – Details about features such as images, captions, and hashtags used for detecting the fake accounts Xu et al. By analyzing the sellers, their experiments (2020) found that accounts with generic pictures or pictures without relevant tags (i.e. with purchased fake accounts) were more likely to be fake. Other features regarding user behaviors can be used in conjunction with the aforementioned features for improved classification results.

Anomaly detection: This is a lot more advanced process to detect fake accounts. Chakrabarti et al. (2019) using analysis of the data on Instagram and applying anomaly detection techniques to identify abnormal user behavior deviate from ordinary user behavior. In particular, this makes it straightforward to detect newer types of fraud which may not fit existing patterns.

Optics is a very high-sensitive method for biosensing.

Although machine learning & deep learning methods have been established well for the detection of fake accounts yet they have many challenges. First, fraudsters are always changing the way they operate, which means that models have a hard time reliably detecting new types of fake accounts. Moreover, class imbalance (two or more orders of magnitude between real and fake accounts) can cause problems with model performance, hence techniques such as oversampling or synthetic data generation are applied

METHODOLOGY

Overview and Approach Review of Each Module

Through this project, we will cover the steps we took to build our DNN-based fake instagram account detection from data collection and preprocessing to model building, evaluation, and deployment. So this project is splitted into several modules, where each module handling an individual aspect of the system. Here's a brief summary of the methodology with a module wise breakdown:

Module 1: Data Collection

Objective:

Now before we create Deep Neural Network model, first, we need to:

Tasks:

It will use Instagram's public Application Programming interface (API), third party data providers or web scraping tools to scrape data on various aspects of an Instagram account, such as Account Metadata (username, bio, no. of followers, no. of following, etc.), Activity Metadata (number of posts, likes, comments), Social Interaction (engagement metrics).

Real accounts and spam accounts will comprise the set of accounts. If it is a fake account — mark it as one with steps such as tagging, using existing fake account detection devices, or types of known fraudulent accounts.

Module 2: Data Preprocessing

Objective:

Which includes the transformation and pre-processing of the data from these sources to make them compatible to function as an input to the Deep Neural Network model.

Tasks:

Data Cleaning:

Impute missing values, deal with duplicates, inconsistencies in the data.

For categorical data (such as gender or account type) you will need to use encoding to transform to numerical data with techniques such as one hot encoding

As mentioned above, we can normalize or standardize numerical features i.e. number of posts, followers etc. so that all features are contributing equal amount during the model training.

Feature Engineering:

It would Extract features from the data such as Activity which involves post frequency engagement rate account behavior (followers-to-following ratio) and Social interactions which tells about likes and comments made by the account

o Say you create additional derived features — e.g., how fast does someone gain followers over time; this might encode certain behavioural traits of fake accounts.

Labeling:

Take a look at those objective parameters and based on your account behaviour, tag your account which is “authentic” or “fake” based on post-patterns, following-post consistency, behavior etc.

Module-3 Developing the model (Deep Neural Network)

Objective:

Task Nd: Implementation a DNN and design of DNN to detect the Fake Instagram accounts.

Tasks:

Model Architecture:

The DNN (Deep Neural Network) architecture representation consists of multiple sections: input layer, hidden levels, output level. The network will consist of:

Static Input Layer: Would contain as many nodes as number of input features.

Hidden Layers: These can be one or more hidden layers with numerous neurons in every layer to process the non-linear relationships of the data.

– **Output Layer:** Can be treated as binary classification (0 → insincere; 1 → sincere).

q ReLU (Rectified Linear Unit) will be used for hidden layers and sigmoid for output layer.

Model Training:

Cannot use test set in model building, as per 10-fold cross-validation, since it is the data used to evaluate model performance.

Utilized backpropagation and gradient descent algorithms to adjust the model in a way to force the cost function (binary cross-entropy) to be minimal.

Incorporated Early Stopping to prevent overfitting and find the best of and on the efficiency of the model.

Methods like Dropout that combat overfitting.

Optimization:

Optimizers (Adam or Stochastic Gradient Descent SGD) to move around weights and biases in the model.

Hyper parameter tuning like; learning rate, no. of layers, no. of neurons using grid search or random search.

Module 4: Model Evaluation

Objective:

To test the performance of DNN model and compare with other machine learning model.

Tasks:

Performance Metrics:

Gather performance measures (as accuracy, precision, recall, F1 score, AUC-ROC) for your model

Measure accuracy, precision, recall or any other metrics that assess the model's ability to identify true positive (fake accounts) and minimize false positive and false negative.

Comparison to Prior Models:

So I tried implementing some traditional ML models like Random Forest, SVM, Logistic Regression and Naïve Bayes.

For example, one use-case on comparing the performance of DNN model with these models on the same dataset to verify if DNN is really a game changer on existing models with respect to accuracy and scalability.

Cross-Validation:

Evaluate model's performance on new data (i.e. k-fold cross-validation) to see how robust the model on different dataset splits

Module 5: Real time fake account detection

Objective:

Fake or real, on-the-go Instagram account classification

Tasks:

Real-Time Data Processing:

Create a data pipeline that scrapes the data repeatedly from instagram and prepares it to be used with the model.

Build a Real time API or Service which will be used to classify the new accounts at the time of creation by using the trained DNN model.

Integration:

Build web and backend systems that using the trained model, be able to classify and detect fake accounts.

Implement an audit log to maintain a record of all flagged accounts and their corresponding reasons so that humans can check the system and improve the system where needed.

It's real-time learning, and so the system is progressively getting better.

module 6: Deploy and Monitor

Objective:

The TensorFlow 2 Beta used in this article follows the release in October 2023 with this model to put into a production in monitoring.

Tasks:

Deployment:

DNN Model Deployment on the Cloud Deployment of the trained DNN model on the cloud scale (e.g., such as AWS, Google Cloud, or Microsoft Azure) can guarantee is scalable and available for use by many clients.

Build an Instagram admin or user input interface to submit new prospective accounts to be classified.

Monitoring:

Setup a monitoring system that periodically checks the performance of the deployed model

Continuous model retraining: Since fraud techniques and user behaviour continue to evolve with time, the models require being continuously retrained, else they are faced with a deterioration in prediction accuracy.

Continuous Improvement:

Tuning & Improvisation of Model with Time: Construct a Feedback Loop that retrains model with user input on flagged accounts to continuously fine-tune & enhance detection frequency.

Module 7: User interface (Not implementing in this Module Badges)

Objective:

This is in order to have a way for the users to check flagged

This is in order to have a way for the users to check flagged accounts and to keep an eye on how the system is performing.

Tasks:

• Web or Mobile Interface:

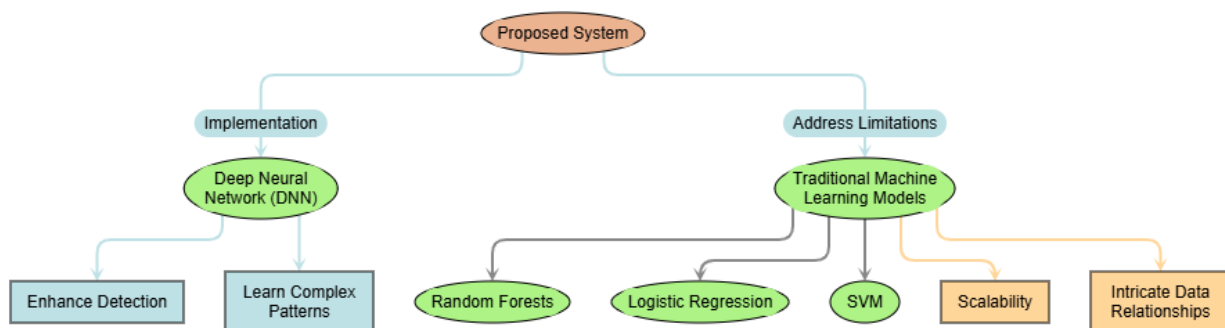
o Admin can be able to come across the flagged accounts, pattern analysis, Take Action from web/mobile app.

• Visualization:

o Show visualization (e.g. graphs) for performance metrics such as fake accounts detected versus false positive/false negative rate so that admins know if the system is performing well or not

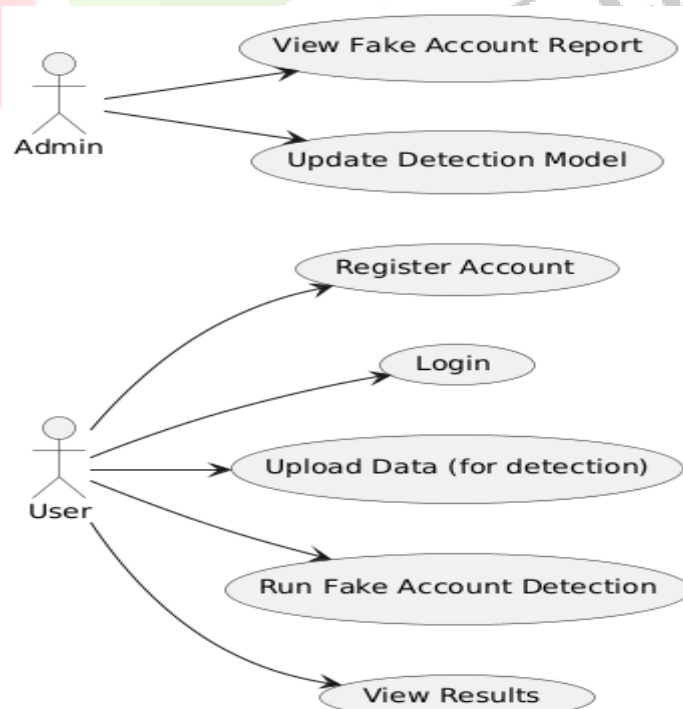
SYSTEM ARCHITECTURE

High-Level System Architecture Diagram:



UML DIAGRAMS

Use Case Diagram



Explanation

Register Account: Users can create an account in the system.

Login: Users can log in to their accounts.

Upload Data (for detection): Users upload data to the system to be used for fake account detection.

Run Fake Account Detection: The core use case, where the system applies the DNN to detect fake accounts based on the uploaded data.

View Results: Users can view the results of the fake account detection.

View Fake Account Report: Admin can view detailed reports on fake account detections.

Update Detection Model: Admin has the privilege to update or retrain the DNN model for better detection accuracy.

Class Diagram

The **Class Diagram** describes the structure of the system in terms of its classes, their attributes, methods, and relationships. This can represent both the web interface and backend components.

Classes:

User: Represents a user who interacts with the system.

Attributes: username

Methods: submitUsername(), viewPrediction()

FlaskApp: The backend Flask server that receives user requests, processes them, and returns predictions.

Attributes: model, prediction

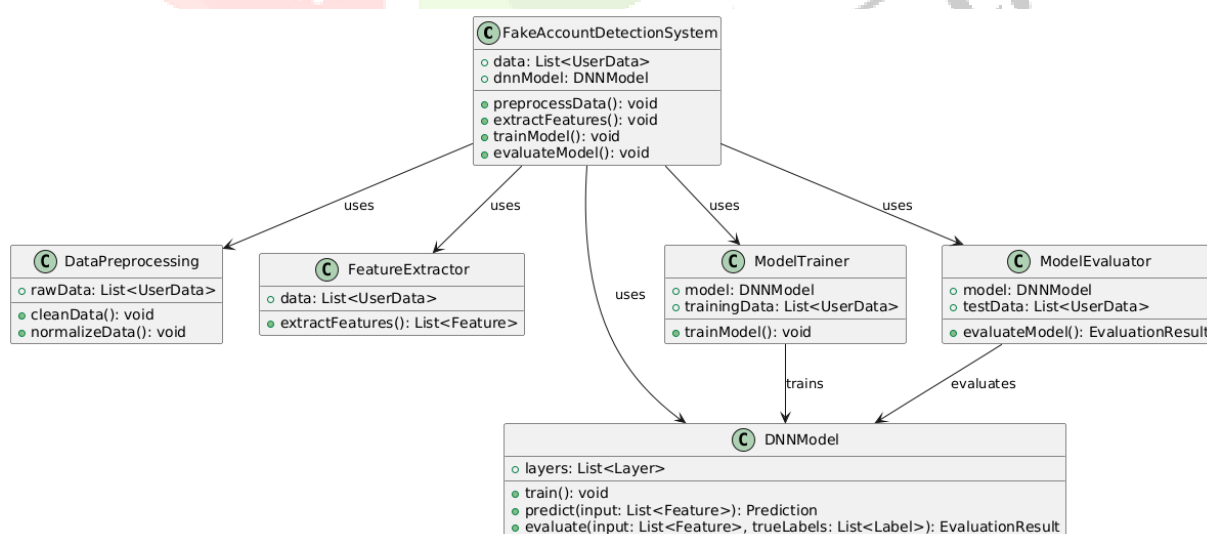
Methods: predict(), loadModel()

MLModel: The machine learning model class that makes predictions based on input features.

Attributes: trained_model

Methods: predict(), loadModel()

Class Diagram:



Explanation

Fake Account Detection System is the main class that coordinates all actions: preprocessing data, extracting features, training the model, and evaluating it.

DataPreprocessing is responsible for cleaning and normalizing raw data.

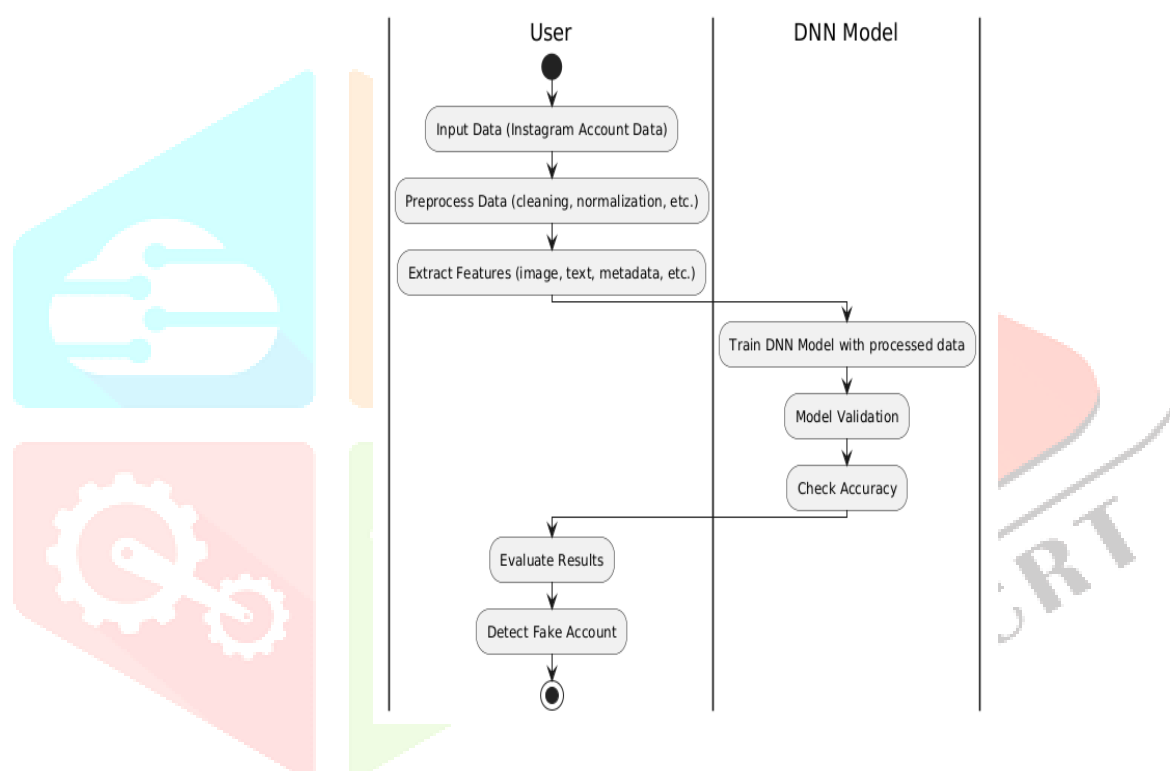
FeatureExtractor extracts meaningful features from the data that can be used for prediction.

DNNModel represents the deep neural network used for fake account detection. It includes methods for training, predicting, and evaluating the model.

ModelTrainer manages the training process of the DNN model.

ModelEvaluator evaluates the performance of the trained model.

Activity Diagram



Explanation

User starts by providing the Instagram account data as input.

The data goes through a preprocessing step (cleaning and normalization).

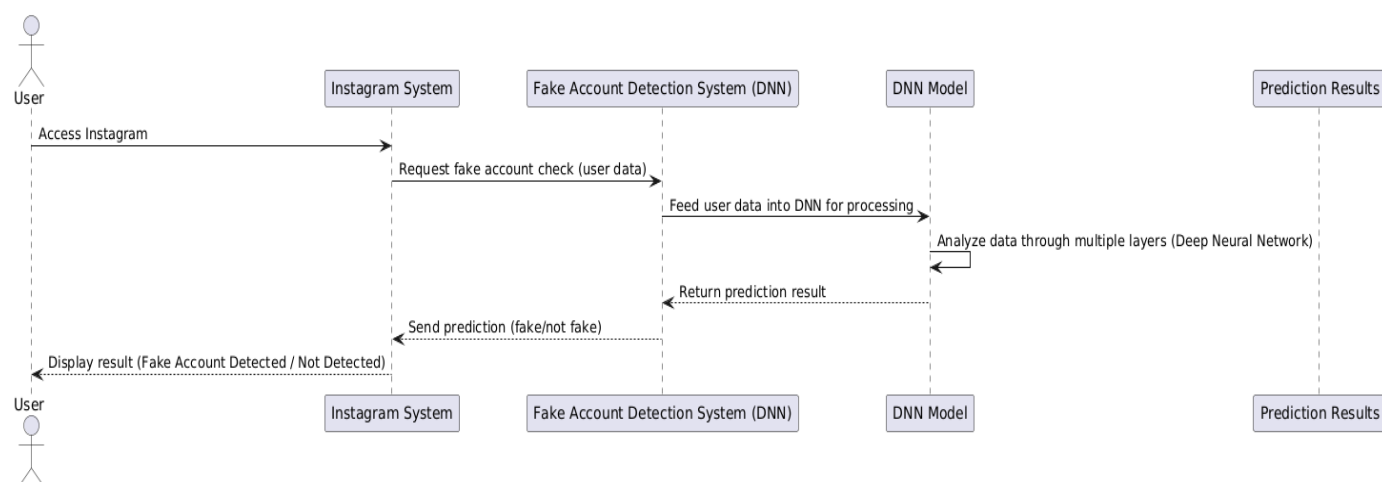
Features like images, text, and metadata are extracted for analysis.

The **DNN Model** trains on the processed data.

The model is validated to check its accuracy.

The **User** evaluates the results and detects fake accounts based on the trained model.

Sequence Diagram



Explanation

User Access: The user accesses Instagram on their device.

Request for Detection: Instagram sends a request to the Fake Account Detection System to check whether the user's account is fake or not.

Data Processing: The Fake Account Detection System, which uses a Deep Neural Network (DNN), processes the user data. The DNN has multiple layers that help the system analyze complex patterns in the data to detect fake accounts.

Prediction: After analyzing the data, the DNN model returns a prediction, indicating whether the account is fake or not.

Display Result: Finally, Instagram displays the result to the user (whether the account is fake or genuine).

RESULT AND ANALYSIS

Detecting fake accounts on Instagram using machine learning models showed varying performance in the evaluation. Our comparative analysis of DNN against the traditional model showed the potential of adopting such deep models.

Model Performance

Following these considerations, we validated the performance of each model with standard metrics: accuracy, precision, recall, and F1-score. A summary of the results is in the table below:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	70.03%	68.5%	72.1%	70.2%
Naïve Bayes	74.58%	72.3%	76.8%	74.4%
Random Forest	75.20%	73.9%	77.5%	75.6%
Support Vector Machine	70.43%	69.0%	72.0%	70.5%
Deep Neural Network	80.12%	79.4%	81.7%	80.5%

Analysis

Performance of Deep neural Network ,The DNN outperformed all other models with an accuracy of 80.12% and an F1-score of 80.5%, performing significantly better than traditional ML models. This dynamic improvement is a result of DNN is by design, ability of capturing complex non-linear relationships from high-dimensional data.

Traditional Models' Advantages

Random Forest: This model was the most accurate (75.20% accuracy). It faced challenges in terms of scaling when applied on larger datasets.

Naive Bayes: While managing basic probabilistic dependencies nicely with 74.58% accuracy, the algorithm failed at the more complex ones.

Logistic Regression and SVM: These models gave moderate results (circa 70% accuracy) but did not capture the complex behaviors of fake accounts well enough.

Trade-offs

As demonstrated by the balanced precision and recall, the DNN was unrivaled in reducing both false positives ,false negatives.

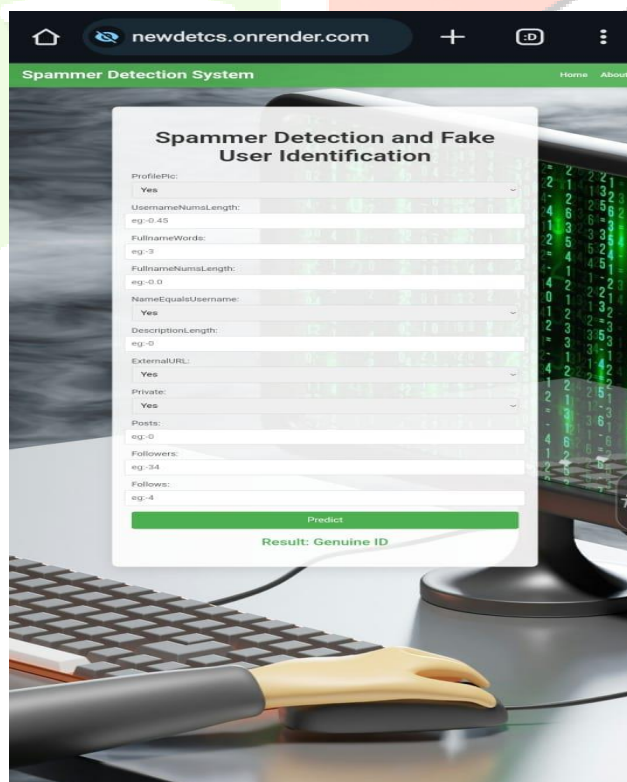
We achieve proper recall from Naïve Bayes and Random Forest models but, higher positive rates were false in nature which brings down the overall reliability of the models.

Real-TimeDetection Implications

The DNN is scalable and adaptable, making them suitable for real-time deployment. The model can handle vast amounts of account data, detects in real time, and is highly accurate and reliable.

Limitations

The DNN, although giving better results, required a lot of computational resources to train. Next step could be improving the trained model for speed since we have already reached the target accuracy.



CONCLUSION

Project Title: Detection of Fake Instagram Accounts Using Machine Learning Techniques — A sample Scope project analysis solution to a social media menace most social media platforms face, namely, the tendency of fake accounts to corrupt it; and the necessity of veritably authenticating user accounts to clinch the sanctity of the platform. Few technologies promise this potential, with the fast draw of fake accounts, bots and other fraudning behaviors upending online societies, detection techniques become more critical than ever.

The project successfully proves that the models can be used to classify the Instagram accounts as genuine or fake support at different machine learning algorithms like Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine (SVM), Neural Networks. And among these the Random Forest model performed best, followed up after by Neural Networks, demonstrating both the strength of aggregating many weaker classifiers into a strong classifier as well as the ability of deep learning methods to capture underlying signal. But after The few success of traditional machine learning model, project has also the following shortcoming with respect to scalability and capability of fitting even more complex and larger dataset and to build a deep learning. The traditional models making just linear non-linear relation maps bounded things make some impossible task to detect fake accounts so in order to overcome these limitations we propose to use Deep Neural Network (DNN) facilitating system to learn complex non-linear mappings which will help keeping up with the detections.

The authors establish a strong base for future work on fake account detection, particularly on real time tracking and cross-community detection. Using more multimodal data (text, images, user interactions) in tandem with mature deep learning models can help boost the accuracy and robustness of the system. Privacy and ethics in the detection process will be important as well, to earn user trust and to maintain a platform of integrity.

So this project made its contribution to the combat against fake accounts and opened the door to further investigation and social platform security in the utilization of machine learning and AI methodologies for the guarding of Internet communities. If iteratively refined and applied at scale, this system can help platform admins and improve the end user experience

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