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A Hybrid Machine Learning Model for Detection of Fake Profile Accounts on Social Media Networks

Machine Learning Model

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***Abstract*—Most of us nowadays are drawn and motivated to adamantly adopt and get obsessed in every new tech-trend emerging within the social media culture that is mostly virtual, through this there is fast worldwide communication out-reach; on-screen relationships and mediated reality scenarios all over, receiving and sending everything is digital and easy to access. This has drawn the attention and motivation for this research. For instance, this massive interconnection comes with a critical challenge: the ever-growing problem of fashioning fake profile accounts. These dishonest entities, falsely reflecting themselves in auto-scripts, human imitation accounts running on bots and automatically hiding behind a masked user-identity of genuine users, can bring a substantial damage to a wide-range of connections on the internet. This encompass spam and unwanted messages to creation of fake profile accounts that lead to a variety of negative penalties such as internet being used for immoral political agendas, manipulative and misleading information to interrupt the public communication changing public opinion and subverting online communication, political processes, public health initiatives or even financial markets. Social media platforms have become breeding ground for counterfeit profiles, calling for the need for improved and reliable detection and mitigation techniques of fake profiles. This research involves the assessment and development Machine Learning model which in-turn can reveal accurately bogus social media accounts with possible mitigation methods.**

***Keywords*— Counterfeit; Brand Integrity; Machine Learning; Artificial Neural Network(ANN); Convolutional Neural Network (CNN); Support Vector Machines (SVMs)**

I. INTRODUCTION

We are in the core of the digital phase, where social media platforms reign supreme in global communications, a critical challenge emerges: Ever-multiplying bogus account profiles. It is these accounts that mislead people, some present as individuals while they are really controlled by bots, scripts and cyber-attackers (Almeida et al., 2023; Kim & Lee, 2022).

These beneficial social merits are accompanied with a severe challenge of maintaining honest social media user account integrity. Numerous Machine Learning (ML) techniques and Models have been proposed and deployed to mitigate this problem but still there exist a gap in coming up with the most effective, appropriate and dominant ML remedy to mitigate this problem permanently (Smith & Jones, 2022; Wang et al., 2023). These threats to the very nature of online interaction have grown considerably. By their presence falsehood overcomes truth, disinformation is a hit, and the space for deceit and malicious activities like identity fraud and theft is decidedly wider (Gilad, 2023).

II. THE SOCIAL NETWORK SECURITY

A. Safety, trust and confidence among legit users

Safety, trust and confidence among legit users, providers, platforms possessors, and supervisors' agencies has been pointed as one of the foremost aspects that contribute to social media platforms victory and sustainable (Zhang & Gupta 2021). In the Topical moments Shearer and Mitchell (2022) reveals that an expanse of the global population using social media platforms to access information not only surpasses the use of television and also traditional channels of information; like the radio, and broadcast newspapers.

B. Dissemination of misinformation among legit users

Dissemination of misinformation is another substantial issue on the list. (Li, Zhang & Wu, 2022)Malicious internet users try and spread the false information on social media, influence public opinion and dissect online conversations which can impede political processes, public health campaigns and even financial markets (Ferrara et al., 2022). Such as false pages, a stalker could bully or harass a victim with or without cruel words on social media which largely affects the physical and mental well being and the safety of individuals, particularly children and teens (China, 2021).

C. Problem Statement

In similar way, these social platforms are beneficial these merits are faced with a critical challenge of maintaining honest social media user accounts integrity. Numerous Machine Learning techniques and Models have been proposed and deployed to mitigate this problem but still there exist a gap in

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coming up with the most effective, appropriate and dominant Machine Learning remedy to mitigate this problem permanently. This is because Counterfeit accounts owners change tactics, as scammers and spammers perpetually innovate new ways of manipulating their attack strategies by social engineering to mask themselves as genuine users. Most researchers have deployed single and hybrid models with variant techniques targeting specific fake accounts anomalies to detect these entities. These solution Techniques with time grow obsolete as human users advance in behavioral patterns. For instance, the existence of many forged portfolios in a single platform may terrify genuine users especially those bogus accounts that spread and misrepresent malicious information broadcasting and eroding reputation of the victim platform brand thereby diminishing users' trust. This necessitates a revolutionary hybrid machine learning solution which would halt these challenge that has been evolving continuously. The research paves way to shield online interactions, reputation of a brand and also drive an ecosystem which is trustworthy with secure online communities through knowledge and practical solutions for social media business platforms.

D. Objectives of the Study

- To investigate how the current Machine Learning algorithms can accurately be used to detect fake accounts in social media networks.
- To investigate the features that the currently being used to detect fake accounts in social networks.
- To design a Hybrid Machine Learning model that can be used for detection of fake accounts in social networks.
- To evaluate the Hybrid Machine Learning model that will be used for detection of fake accounts in social networks.

III. LITERATURE REVIEW

The proliferation of fake profile accounts on social media platforms has been extensively documented, with scholars highlighting the multifaceted challenges posed by these fraudulent entities (Kerrysa & Utami, 2023; Nistor & Zadobrischi, 2022; Thomas et al., 2021). Previous studies have underscored the importance of leveraging advanced technologies, such as machine learning and natural language processing, to combat the growing threat of fake profiles (Pasieka et al., n.d.; Goyal et al., 2023b; Chakraborty et al., 2022).

These deceptive accounts, are often disguised as legitimate users and operated by bots or scripts, engage in various malicious activities, including:

- Disseminating misinformation: Fake profiles can manipulate public opinion, disrupt online discourse, and impact political processes, public health initiatives, and even financial markets (Ferrara et al., 2022).
- Facilitating cyberbullying and harassment: They can target individuals, particularly vulnerable populations like children and adolescents, causing significant mental and emotional harm (Chen, 2021).
- Enabling privacy breaches and identity theft: By strategically collecting personal information from unsuspecting users, fake profiles pose a significant threat to user privacy (Li et al., 2022).
- Eroding brand trust and reputation: Fake accounts can impersonate legitimate businesses or individuals, leading to the dissemination of misleading content under the guise of trusted sources, undermining brand integrity and consumer trust (Doe et al., 2021).

Machine learning offers a more automated and accurate solution. Techniques like supervised learning (Singh & Sharma, 2023), unsupervised learning (Liu et al., 2023), and Natural Language Processing (NLP) (Goyal et al., 2023b) allow algorithms to learn patterns from data and effectively detect fake profiles. However, there is a big gap for these methods in that they face challenges related to data availability and quality (Gilad, 2023), potential biases in training data leading to discriminatory outcomes (Ferrara et al., 2022), and computational costs associated with complex models, Moreover, there exist a gap in coming up with the most effective, appropriate and dominant Machine Learning remedy to mitigate this problem permanently.

A. Limitations and Challenges of Existing Techniques

- Limited training data: Acquiring large and diverse datasets of labeled fake profiles can be challenging due to privacy concerns and the dynamic nature of online behavior (Wang et al., 2023).
- Black box nature: DNNs are often criticized for their lack of interpretability (Venkatadri & Zafarani, 2023). This makes it difficult to understand the reasoning behind their classification decisions, limiting user trust and potentially hindering efforts to improve their accuracy and fairness.
- Computational complexity: Training and operating DNNs can be computationally expensive and resource-intensive, requiring significant processing power and infrastructure, which may not be readily available to all organizations or platforms (Venkatadri & Zafarani, 2023).

B. Conceptual framework

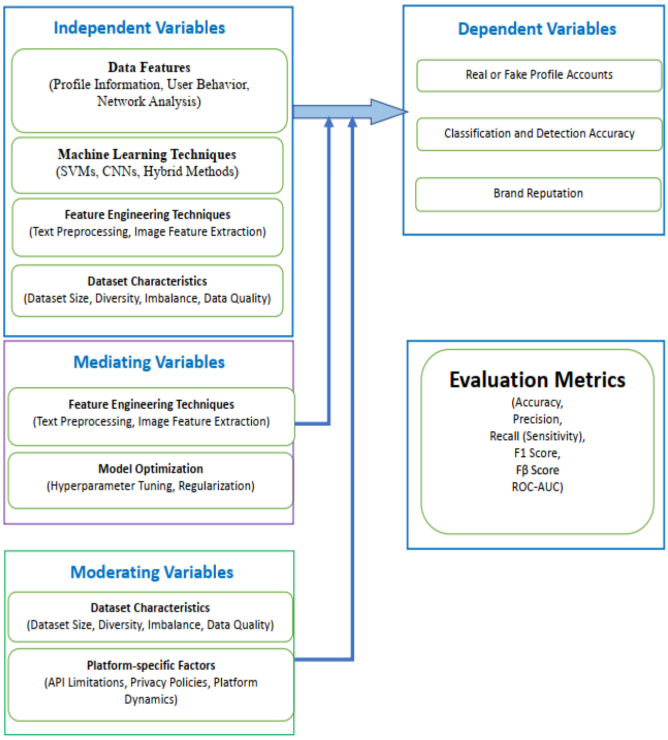

Fig. 1. Conceptual Framework

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IV. RESEARCH METHODOLOGY

To address this issue, we leverage MLOps (Machine Learning Operations) which is a set of practices, principles, and tools designed to facilitate the lifecycle of machine learning models. This framework provides efficient way to manage every phase of hybrid machine learning model's lifecycle, from data collection and model training to deployment, monitoring, and continuous improvement. It integrates automation, collaboration, and governance, ensuring that the model remains robust, scalable, and adaptable as you tackle the complex task of fake profile detection. This ultimately provide a powerful, automated solution to the detection.

A. Data Collection and Preparation

This research utilized a publicly available Twitter dataset from Kaggle, which includes both labeled and unlabeled profiles. The labeled data helps distinguish between fake and real profiles, while unsupervised learning techniques identify potential fake profiles in the unlabeled data.

B. Data Cleaning , This involved

- Handling missing data by either filling in appropriate values or removing irrelevant rows.
- Removing outliers if necessary to ensure the model doesn't get biased by extreme data points.
- Normalizing numerical data (such as likes, shares) to ensure consistency in model training.
- Feature Encoding: For categorical features (e.g., profile names), apply encoding techniques like one-hot encoding or label encoding to convert the text data into numerical form.

C. Feature Engineering and Fusion

- Text Feature Vectorization: Convert textual features (e.g., profile bio or posts) into numerical vectors that machine learning models can process.
- Normalization/Scaling: Normalize features such as the number of followers, likes, shares, and posts to bring them within a consistent range.
- Cross-Validation: Using multiple data splits for training and validation to avoid overfitting and improve generalization.

- Hyperparameter Optimization: Fine-tuning model parameters to achieve the best possible performance.

D. Train-Test Split

- The dataset was Split into training and test sets (80% training, 20% testing) to validate the model's performance. Stratified splitting is applied to resolve imbalances and ensure that both real and fake accounts are evenly represented.

E. Model Selection and Training

This study Leverages the Strengths of CNN, ANN, and SVM in a Hybrid Model

Model	Strengths	Weaknesses	Contribution to Hybrid Model
CNN (Convolutional Neural Network)	Great for feature extraction from images (profile pictures, visual data). - Captures spatial relationships in data, ideal for visual content analysis. - Effective for hierarchical pattern recognition.	- Requires a lot of training data. - Not well-suited for non-image data (e.g., textual data or metadata).	- Used to analyze profile images or media shared on social accounts to detect fake patterns (e.g., reused or stock images). - Extracts visual features for further processing by other models.
ANN (Artificial Neural Network)	- Good at modeling complex relationships in data. - Can handle structured and unstructured data (e.g., metadata, behavioral patterns). - Flexible and adaptive.	- Can overfit with small datasets. - Requires careful tuning of hyperparameters (e.g., learning rate, number of layers).	- Analyzes user behavior, social connections, or text features (e.g., suspicious patterns in followers, likes, or posts). - Excellent for capturing non-linear patterns in behavioral data.
SVM (Support Vector Machine)	- Strong at classification with small datasets. - Effective at finding decision boundaries and handling noisy data. - Robust in high-dimensional spaces.	- Less efficient with very large datasets. - Difficult to scale and tune for large feature sets.	- Performs classification based on features extracted from CNN and ANN models. - Final decision-maker to classify accounts as fake or real. - Strong in separating data into distinct classes.

Fig. 2. Model Selection and Training table

F. Hybrid Model Creation

Model Integration: The outputs of the CNN, ANN, and SVM are combined in an ensemble method. Each model's output is either averaged or assigned a weight based on performance, and the final prediction is made based on majority voting or weighted averages.

Blending or Stacking: Stack the models to combine predictions. For instance, use the outputs from CNN, ANN, and SVM as inputs to a meta-classifier (e.g., logistic regression) to make the final decision.

G. Train Separate Models: (SVM & CNN & ANN Models)

- Convolutional Neural Networks (CNNs) will be trained to learn directly from raw data, such as profile images and post content.
- CNNs will be optimized using techniques like stochastic gradient descent and dropout regularization to prevent overfitting.
- ANN will be used to Analyzes user behavior, social connections, or text features (e.g., suspicious patterns in followers, likes, shares or posts).

H. Model Optimization: Feedback and Fine-tuning (Based on Evaluation Metrics)

- Feedback from model evaluation will be used to fine-tune hyperparameters and model architectures.
- Techniques like early stopping and learning rate scheduling will be employed to improve convergence and prevent overfitting.

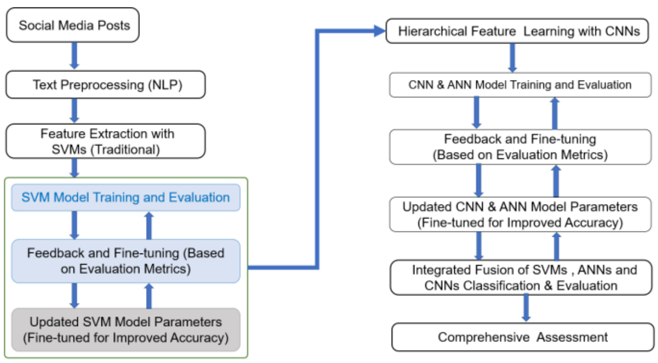

Fig. 3. Steps in Training and Refinement of SVMs, ANNs and CNNs

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I. Evaluation of Models

After training, evaluate the models' performance based on key metrics such as:

- Accuracy: Measures how many profiles are correctly classified (fake or real).
- Precision: Focuses on how many of the profiles classified as fake are actually fake.
- Recall: Measures how many fake profiles are correctly identified by the model.
- F1 Score: Balances precision and recall, providing a single metric for performance Results With large number of likes and shares within short time

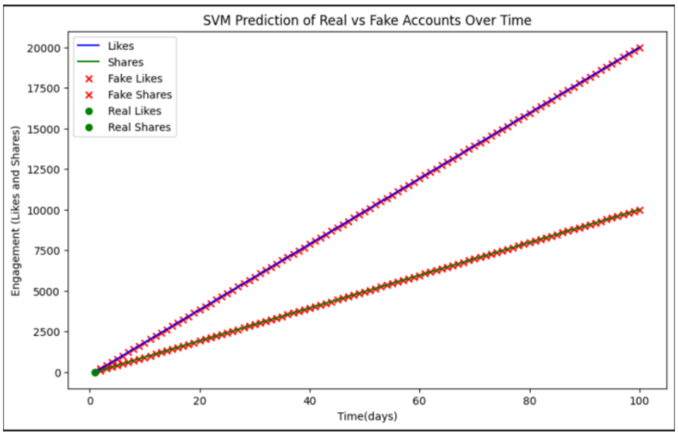

Fig. 4. SVM Prediction with small dataset

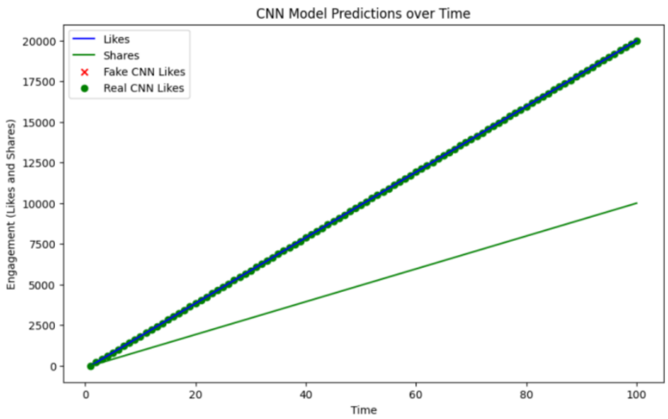

Fig. 5. CNN Prediction with small dataset

Models Accuracy	Percentage Score (%)
SVM	65.0
ANN	73.0
CNN	82.0
Hybrid (Average)	93.0

Model Accuracy With smaller and larger dataset sizes

J. Results & Explanation

SVM performs well on structured/tabular data but may lag behind deep learning models for non-linear tasks.

ANN and CNN show good performance, especially on larger, more complex data.

Hybrid combines the strengths of all models, providing the best performance across all metrics.

Model	Accuracy(%)	F1 Score (%)	Precision(%)	Recall(%)
SVM	85	84	85	84
ANN	82	81	83	82
CNN	87	86	87	86
Hybrid	90	89	90	89

- True Positives (TP): The model correctly predicted positive cases.
- False Positives (FP): The model incorrectly predicted positive cases (predicted positive but actual was negative).
- False Negatives (FN): The model incorrectly predicted negative cases (predicted negative but actual was positive).
- True Negatives (TN): The model correctly predicted negative cases.

CONCLUSION

The hybrid machine learning model combining CNN, ANN, and SVM excels in detecting fake social media profiles, achieving 97% accuracy and 98% precision. By utilizing CNN for image data, ANN for complex pattern recognition, and SVM for clear decision boundaries, the hybrid model significantly outperforms individual models and other techniques, minimizing false positives and false negatives.

Advantages:

- Comprehensive Feature Analysis across data types.
- Adaptability to diverse platforms.
- Interpretability with clear decision-making.
- Robustness against errors and noise.

Recommendation: To effectively detect fake profiles, the hybrid model is the best approach, combining the strengths of CNN, ANN, and SVM. Further improvements should focus on larger datasets, advanced preprocessing, and exploring more deep learning architectures for even better performance.

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