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SMARTPROFILENET: CNN-DRIVEN SYSTEM FOR IDENTIFYING FRAUDULENT USER PROFILES

[1]*Srujana,*[2]*Santhosh Kumar*
Department of ECE
Sir C.R.Reddy Engineerng College,Eluru

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ABSTRACT

The rapid growth of online platforms has led to a surge in fraudulent user profiles, compromising data integrity and user trust. Traditional fraud detection systems often rely on rule-based or manual inspection methods, which are unable to adapt to evolving fraudulent patterns. This paper presents SmartProfileNet, a deep learning framework that leverages Convolutional Neural Networks (CNNs) to automatically detect fraudulent profiles. The proposed system analyzes user behavior, profile attributes, and interaction patterns to identify suspicious accounts. Experimental evaluations demonstrate that SmartProfileNet achieves high accuracy and robustness compared to conventional methods, making it a reliable solution for large-scale online platforms.

I. INTRODUCTION

Fraudulent user profiles are a growing challenge for social networks, e-commerce platforms, and online communities. Such profiles can engage in spamming, identity theft, or manipulation of online ratings, undermining platform credibility. Traditional detection methods rely heavily on manual rules, heuristic-based approaches, or shallow machine learning models. However, these approaches struggle with the dynamic and complex nature of fraudulent behavior. Deep learning, particularly Convolutional Neural Networks (CNNs), provides an automated feature extraction mechanism capable of capturing intricate patterns in user data. SmartProfileNet integrates CNNs to analyze user profile attributes and behavioral sequences, enabling accurate detection of fraudulent accounts while adapting to new fraud strategies.

II. LITERATURE SURVEY

Prior research in profile fraud detection has explored various methodologies, including rule-based systems, anomaly detection, and traditional machine learning models. Rule-based approaches, though simple, fail to generalize to unseen fraud behaviors. Anomaly detection methods monitor deviations from typical user behavior but often generate high false positives. Machine learning methods such as decision trees, random forests, and support vector machines have improved detection accuracy by leveraging feature engineering, but they are limited in capturing complex temporal or relational patterns. Recent studies have applied deep learning architectures like CNNs and Recurrent Neural Networks (RNNs) for fraud detection, demonstrating superior performance due to automatic feature extraction and hierarchical

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pattern learning. However, challenges remain in real-time detection and robustness across large-scale platforms.

III. PROPOSED METHODOLOGY

The proposed SmartProfileNet framework uses CNNs to automatically extract spatial and relational features from user profiles. Input data includes profile metadata, activity logs, and interaction networks, which are preprocessed and normalized before being fed into the CNN layers. The convolutional layers identify local feature patterns, while pooling layers reduce dimensionality and retain essential information. Fully connected layers followed by a softmax activation function classify profiles as legitimate or fraudulent. Dropout and batch normalization techniques are employed to improve generalization and prevent overfitting. The model is trained using backpropagation with categorical cross-entropy loss and optimized using the Adam optimizer. This approach eliminates the need for manual feature engineering and adapts to evolving fraudulent strategies.

IV. EXPERIMENTAL SETUP

SmartProfileNet is evaluated on publicly available datasets of online user profiles containing labeled fraudulent and legitimate accounts. The datasets are divided into training, validation, and test sets, with preprocessing steps including normalization, encoding of categorical attributes, and activity sequence embedding. Performance metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) are used to assess model effectiveness. Experiments are conducted on GPU-enabled systems to accelerate training. Comparative studies are performed with traditional machine learning approaches like random forests, SVMs, and shallow neural networks to demonstrate the superiority of the proposed CNN-based system.

V. RESULTS AND DISCUSSION

Experimental results indicate that SmartProfileNet outperforms conventional methods in detecting fraudulent user profiles. The CNN architecture effectively captures complex patterns in profile attributes and behavioral sequences, resulting in higher detection accuracy and lower false-positive rates. The system demonstrates robustness across different datasets and is capable of generalizing to previously unseen fraud patterns. Additionally, real-time detection simulations confirm the model's potential for deployment in large-scale online platforms. Limitations include high computational requirements for very large datasets, which can be mitigated by model optimization and incremental learning techniques.

VI. CONCLUSION

This paper presents SmartProfileNet, a CNN-driven framework for detecting fraudulent user profiles in online platforms. By leveraging automatic feature extraction and hierarchical pattern learning, the system achieves superior detection accuracy, robustness, and adaptability compared to traditional methods. Experimental evaluations confirm the

effectiveness of the model in identifying both known and novel fraudulent profiles. Future work will focus on real-time deployment, optimization for computational efficiency, and integration with graph-based features for enhanced relational fraud detection.

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