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Multi-Modal AI System for Real Time Insider Threat Recognition

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Abstract: Insider threats pose a major cybersecurity risk as they originate from authorized users who misuse access privileges, causing data breaches and financial losses. Traditional rule-based security systems often fail to detect such threats due to evolving user behaviour patterns. This research proposes a deep learning-based insider threat detection system using Long Short-Term Memory (LSTM) networks and Autoencoders. The LSTM model captures temporal patterns in user activity, while the Autoencoder learns normal behaviour and detects anomalies through reconstruction errors. The hybrid approach improves detection accuracy, reduces false positives, and supports effective monitoring of organizational activities. Although the system shows better performance compared to traditional methods, challenges related to computational complexity and real-time deployment remain areas for future work.

Keywords: Insider Threat Detection, Deep Learning, LSTM, Autoencoder, Anomaly Detection, User Behaviour Cybersecurity, Network Security.

I. INTRODUCTION

In today's digital environment, organizations rely heavily on information systems to manage confidential and sensitive data. While external cyberattacks receive significant attention, insider threats pose a serious and often overlooked risk. Insider threats occur when authorized users, such as employees or contractors, misuse their access either intentionally or unintentionally, leading to data breaches, financial loss, and reputational damage. Since insiders already have legitimate access to systems, traditional security mechanisms often struggle to detect their malicious activities. To address this issue, advanced deep learning techniques such as Long Short-Term Memory (LSTM) networks and Autoencoders are increasingly used for insider threat detection. LSTM models are effective in analyzing sequential user behaviour data and identifying unusual activity patterns over time. Autoencoders, on the other hand, are widely used for anomaly detection by learning normal behaviour patterns and identifying deviations from them. Although these approaches improve detection accuracy.

II. LITERATURE REVIEW

Recent research in insider threat detection focuses on advanced AI techniques for improving accuracy and contextual understanding. The most recent work, [1] Insider Threat Detection based on Knowledge Graph and Large Language Model, integrates Knowledge Graphs with LLMs to analyze large scale logs and improve anomaly detection, though it increases computational complexity. Similarly, [2] Insider Threat Detection based on Deep Belief Network Feature Representation uses unsupervised learning to detect multi domain insider behavior without labeled data, but depends heavily on dataset quality. Earlier, [3] Deep Learning Approaches for Strengthening Network Intrusion Detection Systems applied hybrid models like RNN and Bi LSTM to enhance detection accuracy and scalability, though at high computational cost. The review paper [4] Insider Threat Detection Using Deep Learning highlights that deep learning outperforms traditional methods but faces interpretability and real-time challenges. Finally, [5] Detection of Insider Threats using Deep Learning introduced behavior-based anomaly detection using the CERT dataset, providing early detection but with issues like false positives and training complexity.

III. MATERIALS AND METHODS

A. System Architecture

System architecture for insider threat detection using LSTM and Autoencoder generally consists of multiple structured layers that work together to identify abnormal user behaviour. The architecture begins with a data acquisition layer, where user activity logs such as login attempts, file access, email usage, and network activities are collected from organizational systems. This data is then processed in the preprocessing layer, where cleaning, normalization, and feature extraction are performed to convert raw logs into structured sequential data.

The processed data is fed into the LSTM model to analyze temporal patterns in user behaviour over time, while the Autoencoder model learns normal activity patterns and detects anomalies by measuring reconstruction error. The outputs from these models are evaluated in the anomaly detection layer, where suspicious activities are identified based on predefined thresholds. Finally, the results are visualized through dashboards and alert systems, enabling security teams to monitor, analyze, and respond to potential insider threats effectively.

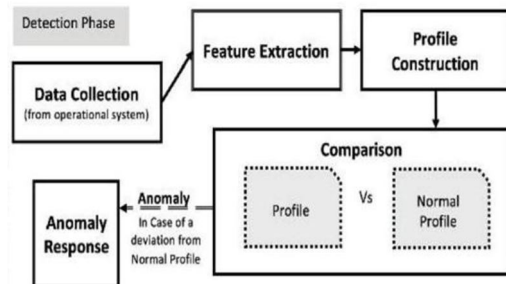


Figure 1: System Architecture

B. Proposed System

The proposed system for insider threat detection is designed using a hybrid deep learning approach that combines LSTM and Autoencoder models to accurately identify anomalous user behaviour. The system begins with the collection of user activity logs, including login details, file access records, system usage, and network activities from organizational environments. These logs are preprocessed through data cleaning, normalization, and feature extraction to convert them into structured sequential datasets suitable for deep learning models. The LSTM model is then applied to analyze temporal patterns in user behaviour and capture long-term dependencies in activity sequences. Simultaneously, the Autoencoder model learns normal behaviour patterns and detects anomalies by calculating reconstruction errors when unusual activities occur. The outputs from both models are integrated to generate anomaly scores, and activities exceeding a defined threshold are flagged as potential insider threats. The final results are displayed on a monitoring dashboard, providing real-time alerts and performance metrics to assist security administrators in effective decision-making and threat response.

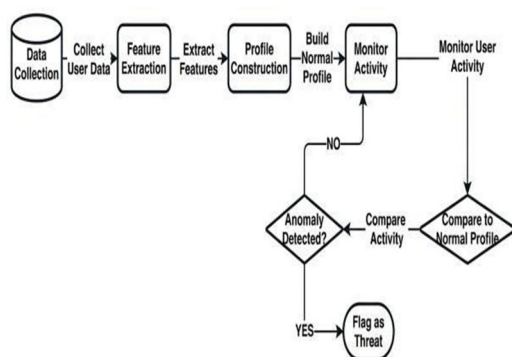


Figure 2: Proposed System

IV. RESULTS AND DISCUSSION

The experimental results show that the proposed LSTM and Autoencoder-based model effectively detects insider threats by analyzing user behaviour patterns. The LSTM model successfully captures sequential and time-based activities, helping to identify suspicious behaviour that develops gradually. The Autoencoder accurately detects anomalies by learning normal behaviour patterns and identifying deviations through reconstruction error. The combined approach improves overall detection accuracy and reduces false positives compared to traditional rule-based systems. However, the system requires high computational resources and large volumes of quality training data for optimal performance. Additionally, real time implementation and model interpretability remain challenges. Despite these limitations, the results indicate that the proposed deep learning approach provides a reliable and efficient solution for insider threat detection.



Figure 3.1: Dashboard

The dashboard provides a visual overview of insider threat detection results, including alerts, anomaly scores, user activity trends, and flagged suspicious behaviours. It helps us understand about the various types of threats, their scores, behaviour analytics etc.

It helps administrators monitor system activity in real time and quickly identify potential threats.

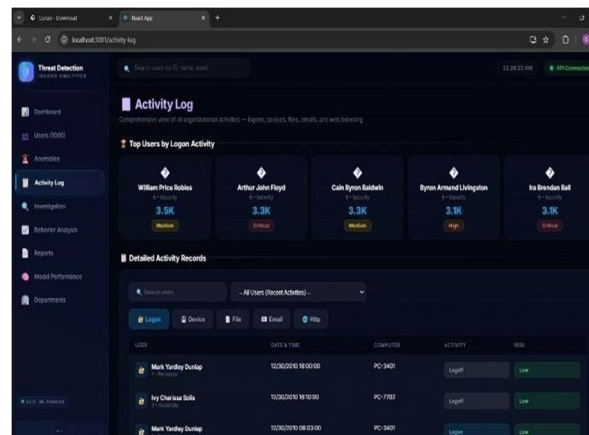


Figure 3.2 Activity Logs

Activity logs record user actions such as login attempts, file access, downloads, and system usage. These logs serve as the primary input data for the LSTM and Autoencoder models to analyze behavioural patterns and detect anomalies.

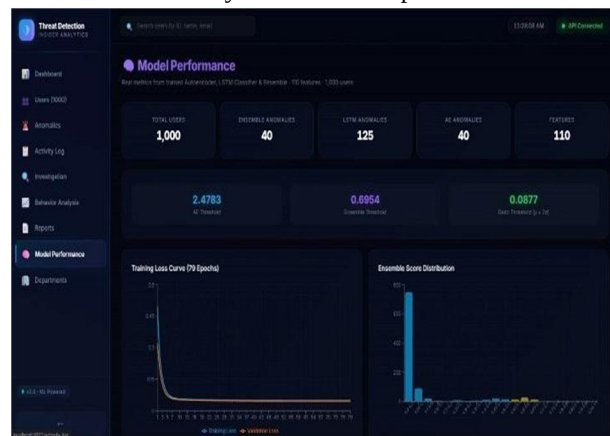


Figure 3.3 Model performance

Model performance is evaluated using metrics such as accuracy, precision, recall, and false positive rate. The LSTM and Autoencoder models show improved detection capability compared to traditional methods, especially in identifying hidden or gradual insider threats.

V. CONCLUSION

To enhance insider threat detection, this study proposes a hybrid deep learning framework combining Long Short-Term Memory (LSTM) networks and Autoencoder models for behavioural anomaly detection. The LSTM model effectively captures temporal patterns in user activities, while the Autoencoder identifies deviations from normal behaviour through reconstruction error analysis. The proposed approach improves detection accuracy and reduces false positives compared to traditional rule-based methods. By leveraging sequential learning and anomaly detection together, the system provides an efficient solution for monitoring insider activities in organizational environments. Future work will focus on reducing computational complexity, improving model interpretability, and enabling real-time deployment for large-scale enterprise cybersecurity systems. Our Insider Threat Detection project outperforms traditional models by using a hybrid approach with CNN, LSTM, and Autoencoder, which together improve detection accuracy. CNN captures complex patterns, LSTM models temporal user behavior, and Autoencoder detects anomalies, reducing false positives and negatives. This combination makes the system robust, adaptable, and capable of identifying subtle insider threats proactively, unlike single-model approaches.

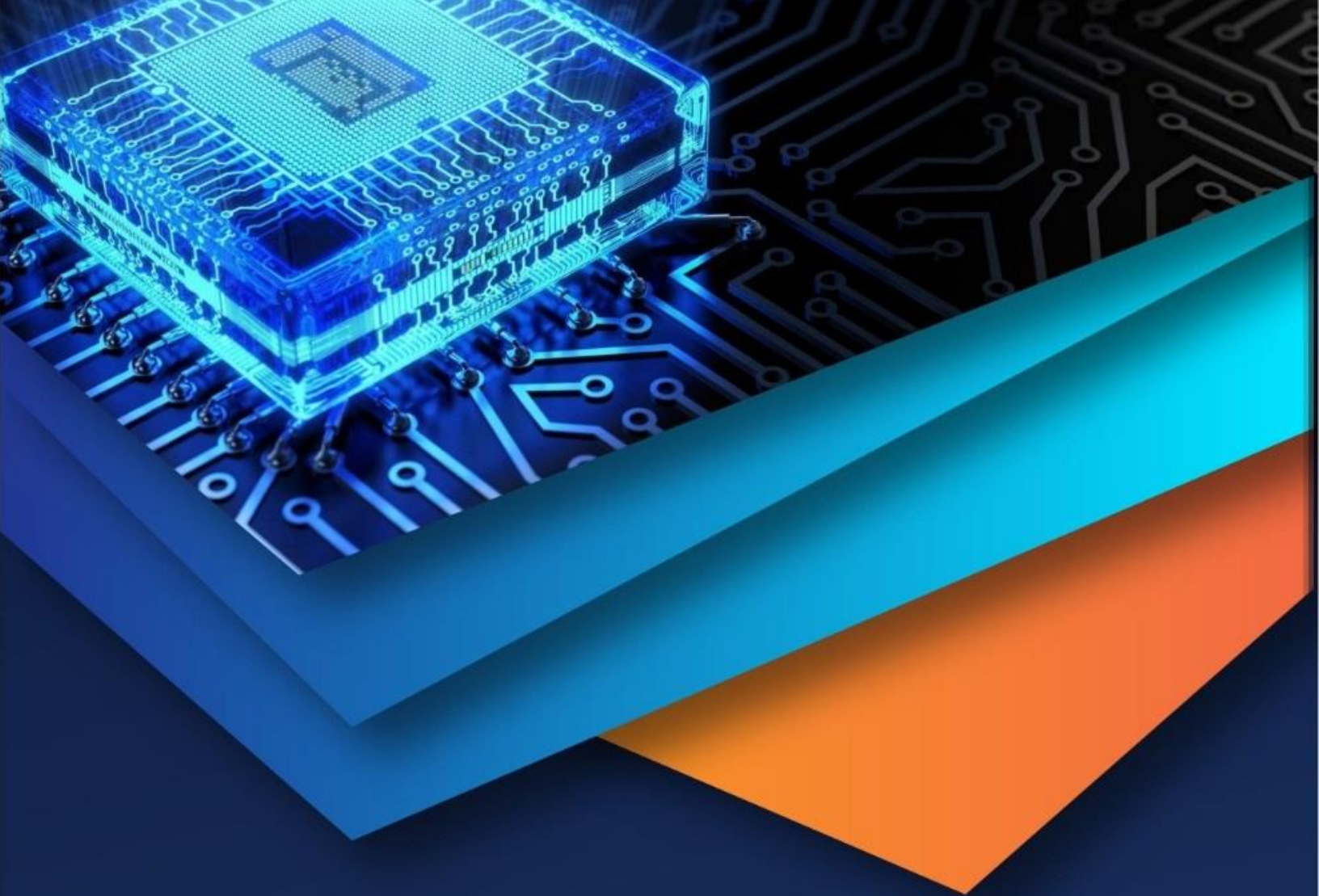
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