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Neural Network-Based Anomaly Detection for Securing Cloud Data Transactions

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ABSTRACT: The sheer revolution that cloud computing has brought in data storage and processing has also brought with it enormous security challenges particularly in maintaining data transactions' security. This study provides an anomaly detection framework based on a neural network specifically to protect the cloud data transactions. The suggested architecture of the model includes a mix of hybrid architecture, a combination of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks and an attention mechanism to capture the most relevant data as found in complex data streams. The CNN layer detects the patterns in space, while Bi-LSTM processes temporal dependencies from both directions, allowing thorough anomaly detection. The attention layer also enhances the precision of detection because the most important segments of data are prioritized dynamically. The model is deployed using TensorFlow and Keras API in python, having high accuracy and low false positive rate and hence has great potential when deployed in real-time. This method offers a smart, scalable solution to the security and integrity requirements of data transactions on the cloud against ever-changing cyber threats.

Keywords: Cloud Security, Anomaly Detection, Neural Networks, CNN-BiLSTM, Attention Mechanism, TensorFlow, Data Transa**ctions**

I. INTRODUCTION

Cloud computing is currently a crucial factor in bringing data-oriented applications and services in all industries. The need for the security and integrity of the transactions of data in the clouds because of its volumetric and complex nature has become even more significant [1]. Although the cloud platforms provide flexibility, scalability, and affordability, there are many underlying cyber threats associated with the cloud platforms, including Distributed Denial of Service (DDoS) attacks, data breaches, and insider threats. Anomalies in cloud data transactions are usually a demonstration of potential security breaches or misconfiguration of computer systems, and hence anomaly detection is one of the key elements in modern cloud security frameworks [2].

Existing rule-based and machine-learning-based intrusion detection systems are unable to adapt, are not accurate and unable to handle large scale and heterogeneous data from clouds [3]. To overcome these challenges, this research presents a new anomaly detection deep learning model based on a hybrid Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM)

networks with an added layer of an attention mechanism [4]. CNN part extracts spatial qualities and patterns from a network traffic flow, whereas Bi-LSTM reads the temporal sequence of the data transactions in both directions. The embedded attention layer emphasizes important details, and thereby, the model will learn to pay special attention to important patterns, which would contribute to anomaly detection as shown in figure 1.

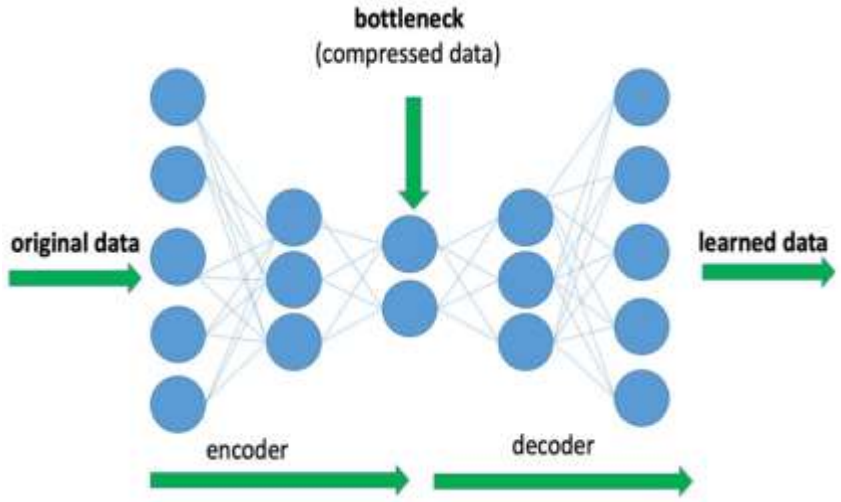

Figure 1. Neural Network-Based Anomaly Detection.

TensorFlow, with the Keras API in Python is used for development and implementation of the model, thereby, offering a strong and scalable environment required for training, validation, and deployment [5]. This strategy is intended to increase the precision, recall and net detection performance while reducing the false positives. Through incorporating spatial, temporal, and contextual learning into a unified model, the suggested system provides an efficient and real-time solution for securing the transactions of cloud data [6]. This research supports the development of smart cybersecurity systems that are able to adjust to the changing scenario of threats in cloud computing settings.

II. RELATED WORK

Anomaly detection in the cloud has emerged to be a critical area of study with the upscale relying on cloud computing to facilitate sensitive data transactions.Table 1 shows the aummary of related work 2025-2018. There are various studies on intrusion detection and anomaly thresholding that used machine learning and deep learning models.

Table 1.Depicts the summary of related work 2025-2018

Year	Authors	Methodology	Key Contributions	Limitations
2025	Ouhssini et al.[7]	DeepDefend framework using DL models (CNN, LSTM, Autoencoders)	Proposed a comprehensive DDoS detection and prevention system with high accuracy.	High computational cost; lacks real-time adaptability.
2024	Pandithurai et al.[8]	Bi-LSTM with Honey Badger Optimization for feature selection	High precision and low false positive rate in DDoS prediction.	Limited to pre-collected datasets; no live network testing.
2023	Aliar et al. [9]	Hybrid DBN-GRU architecture with optimized fused features	Automated detection of DDoS with improved accuracy and low FPR.	Complex architecture may impact real-time deployment.

2023	Bhardwaj et al.[10]	Stacked sparse Autoencoder with DNN and Hyperband tuning	Improved detection metrics on imbalanced datasets.	Requires high training time and computational resources.
2022	Dennis & Priya [11]	Fusion of Deep Belief Network and SVM	Enhanced classification accuracy for DDoS and EDoS detection.	Scalability and generalizability not addressed.
2021	Kushwah & Ranga [12]	Optimized Extreme Learning Machine (ELM)	High sensitivity and low training time for DDoS detection.	Evaluation only on benchmark datasets.
2020	Velliangiri et al. [13]	FT-EHO with Deep Belief Network	Efficient detection of DDoS using hybrid optimization and DL.	Model complexity increases with user count.
2020	Abubakar et al. [14]	SVM with SNORT IPS integration	Real-time DDoS mitigation in both single and multi-source attack scenarios.	Limited evaluation metrics; lacks deployment insights.
2019	Wani et al. [15]	ML-based DDoS detection using standard classifiers	Highlighted performance of ML models for anomaly detection in cloud.	Lack of detailed comparative analysis.
2018	Douligeris & Mitrokotsa [16]	Taxonomy-based analysis of DDoS detection mechanisms	Comprehensive classification of DDoS attacks and defenses.	No empirical model implementation.

Conventional machine learning models including; Support Vector Machines (SVM), Random Forests (RF), and Decision Trees have proved efficacy in recognizing particular forms of attacks but fail to give quality results with complex, high-dimensional and time-series cloud data [17]. Some of the recent techniques have utilized deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks because they have the capacity to learn spatial and temporal features respectively. For example, models that make use of CNNs together with LSTMs have shown better detection accuracy with regard to the identification of both transaction-level anomalies and sequential network behavior patterns [18].

Attention mechanisms have also been used in the learning models such that more focus is given to the most relevant feature or time step resulting in improved model's performance in detecting anomalies. However, a lot of such implementations do not have real-time scalability, or fail to process both spatial and sequential data simultaneously [19]. The use of Bi-LSTM networks expands the learning process through a sequence analysis from both the sides (forward and backward) and thus allows more context for detecting faint anomalies.

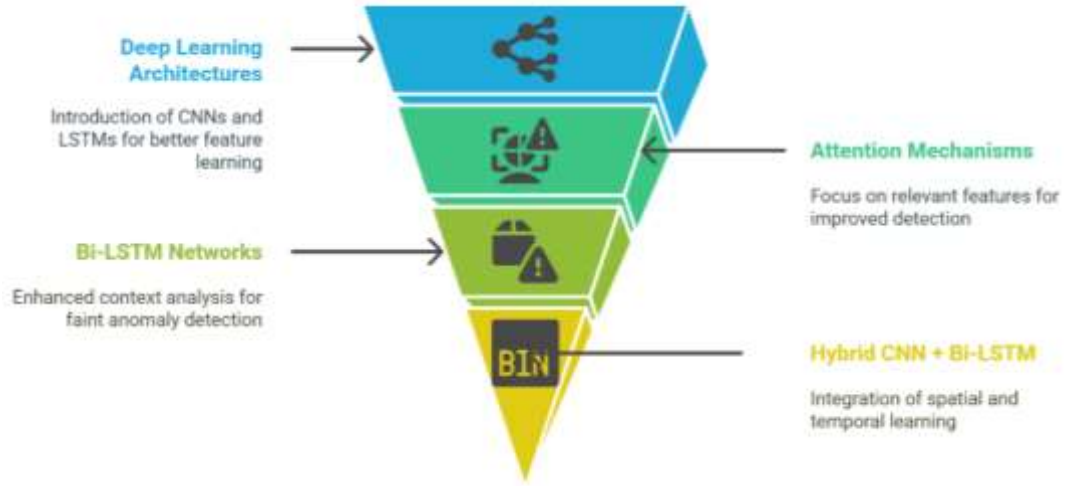

Figure 2.Evolution of Anomaly Detection in Cloud.

On the basis of these foundations, the proposed work develops a hybrid CNN + Bi-LSTM architecture improved with an attention layer. Being implemented with the aid of TensorFlow and the Keras API, this model is aimed at addressing problems of previous approaches through a combination of efficient pattern recognition in spatial domain, sequence learning in temporal domain and dynamic feature selection [20]. This combined architecture is explicitly created to protect cloud data transactions to achieve high accuracy and low false positives and real-time detection abilities making it a strong improvement from prevailing methods in the domain of anomaly detection in a cloud [21].

III. RESEARCH METHODOLOGY

This methodology includes the design and implementation of a deep learning-based anomaly detection model customized for the security of cloud data transaction [22]. The approach is based on hybrid architecture: a combination of CNN and Bi-LSTM with attention mechanism, which has been developed in TensorFlu and Keras API in Python. The system to be developed will be efficient, accurate, and scalable, which will be able to detect malicious activities in clouds.

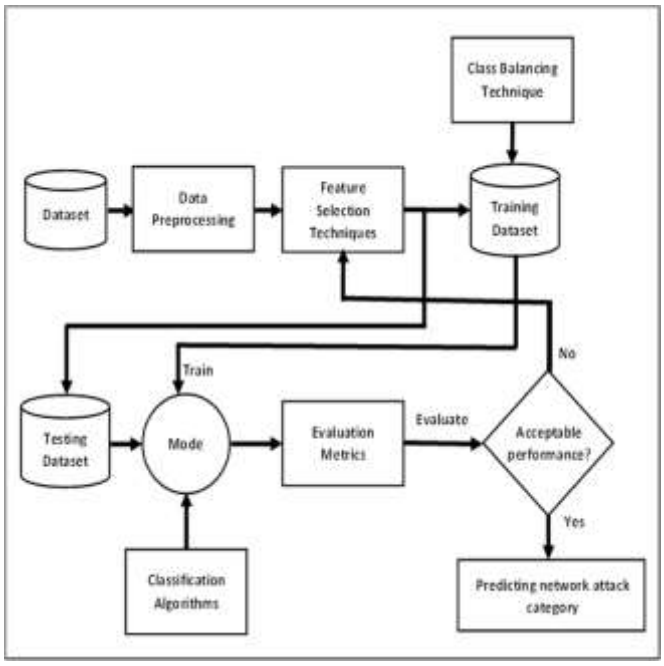

Figure 3.Flow chart of Proposed Methodology.

The following parts are the major components of the suggested methodology for "Neural Network-Based Anomaly Detection for Securing Cloud Data Transactions". Preprocessing makes use of Z-score normalization, normalization of data for the efficiency of neural networks [23]. The feature selection framework has an attention mechanism that can make the model attend to the most relevant features for example unusual transaction patterns. Classifier is a Hybrid CNN + Bi-LSTM having an attention layer, incorporating spatial and temporal relationships and providing improved model interpretability. The methodology is realized on TensorFlow with Keras API, providing such advantages as flexibility, scalability, and optimization for cloud and edge deployment as shown in figure 3. PyTorch is an alternative when it comes to dynamic computation graphs [24].

3.1. DATASET

A publicly available well-designed benchmark datasets such as CICIDS2017, UNSW-NB15 and CSE-CIC-IDS2018 have been used in the study. These datasets are emulation of the real-life cloud transaction contexts and contain various legitimate traffic as well as attack traffic in the forms of DoS, DDoS, and insider threats [25].

3.2 SECURITY ISSUES IN CLOUD NETWORKS

The architecture of cloud computing is based on two major components, front- end and the back- end. The front end is the interface that the users use to make use of the system. At the same time, the back end involves a number of cloud service models, including Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). Fig.4 shows the user types corresponding to every model, as well as uses being under arrangement in them [26].

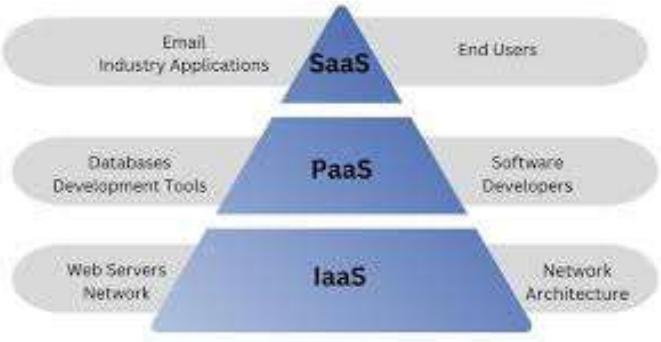

Figure 4. Cloud service models.

A.SOFTWARE-AS-A-SERVICE (SaaS)

This is the first level of service model. Under this cloud, providers provide access to a database and a software but Software-as-a-service (SaaS) suffers from security problems, placing responsibility on users. Users need to be careful with regard to sharing information and access. Lately, cyber threats demonstrate the attractiveness of cloud providers targets and call for the users to apply extra critical scrutiny to the security of their providers DDoS attacks make a substantial threat for SaaS implementations influencing both the provider side and a user's side. Being a prominent model of cloud computing, SaaS raises interest on the part of malicious actors who aim at services disruption. With SaaS, the software is remotely accessed in a central place, making it vulnerable to DDoS attacks, which may be used to overwhelm servers and deny services to the rightful users.

These attacks can sabotage conduct of business operations, cause financial losses and spoil the image of SaaS providers. Deployment of strong security practices such as the use of IDS, firewalls and encryption protocols is extremely important in reducing the threat of DDoS attacks. It is also important to have continuous monitoring and quick response mechanisms to promptly identify and combat those attacks and ensure the SaaS sites' integrity and availability for the users. At the same time, Intrusion detection in

SaaS environments is essential for the protection of the service provider and the service users [27]. SaaS is the case where several people use the same application instance, which presents unique security issues. Traditional IDS may not be able to f it SaaS because of the lack of control over infrastructure. As such, there is a need for context-dependent multi-tenant IDS frameworks.

B.PLATFORM-AS-A-SERVICE (PaaS)

This second layer of the service model known as Platform as a ser vice (PaaS) provides a computing platform that has fundamental characteristics such as the operating system, programming languages, databases as well as web servers. Such resources automatically adjust in dealing with application demands [28]. In this configuration, developers use special Application interfaces (APIs) to develop applications to be used in some specific environment. PaaS also provides software deployment and configuration settings control as shown in Figure 5.

C. INFRASTRUCTURE-AS-A-SERVICE (IaaS)

Infrastructure as a Service (IaaS) is one of the cloud computing models that enables its clients to use virtualized computing resources, including virtual machines, storage, and networking, over the Internet. This service allows organizations to rent IT infrastructure on a flexible pay-as-you-go model that will allow these organizations to scale their resources depending on their needs without the need of sinking resources or handling physical hardware. IaaS, i.e., one of the three cloud service models is very vulnerable to DDoS attacks [29]. The DDoS attacks exploit the fact that these cloud resources are being shared, in order to bombard the infrastructure with traffic and therefore deny access to legitimate users. The DDoS attacks are opposed through a list of processes and countermeasures including intrusion prevention, intrusion detection and intruder response. Due to the security issues related to IaaS in the cloud computing, installation of IDS becomes very necessary to address the same. The strong security measures are also needed to secure the cloud-based infrastructure services, and IaaS-focussed IDS is considered important [30].

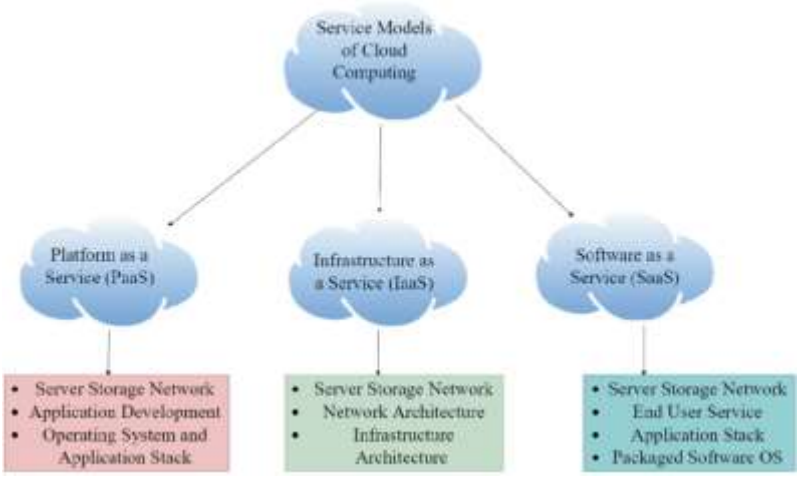

Figure 5.Colud Security using Machine Learning Techniques.

3.3. CLOUD NETWORKS BASED ANOMALY DETECTION

It is abnormalities in a cloud network that speak of deviations from normal patterns, behaviors and occurrences that may suggest security threats, babblings and performance snafus. They are classified to include the likes of unauthorized access, unusual data transmission, and abnormal resource use ranging from the categories of security, network traffic to resource utilization, application behavior, data, and user behavior anomalies. It is important for the integrity, security, and reliability of cloud network to identify and prevent such anomalies to protect the network against cyber threats and ensure proper performance [31]. Various anomalies have been identified in the world of research, which is a big threat to the security structure of cloud networks; among them are the following:

A. Distributed Denial of Service (DDOS) attack

Distributed Denial of Service (DDoS) attack is a cyber-attack which involves placement of multiple systems/devices by attackers to flood a targeted server or network with traffic thus, rendering it inaccessible by legitimate users . DDoS attacks in cloud computing can inflict substantial damage to cloud service providers and their clients, and cause a downtime, a loss of revenue and reputational damage [32]. Hence, there is need to establish adequate detection and prevention apparatuses that will limit the effects of DDoS attacks in cloud computing environments.

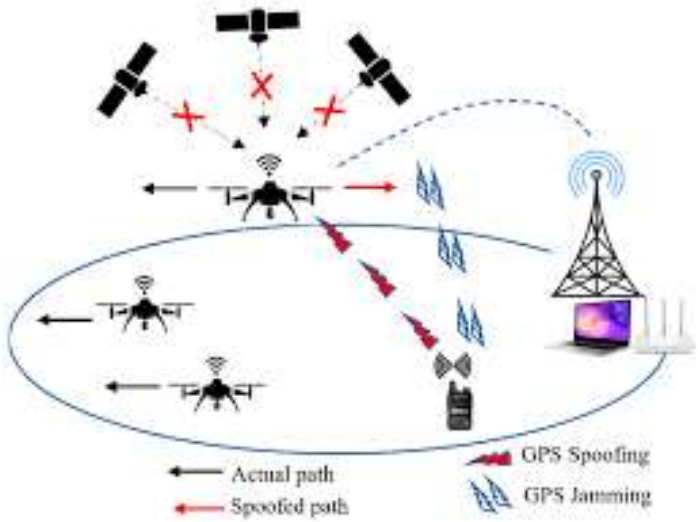

Figure 6. . DDoS attacks in cloud computing.

B. Intrusion Detection Systems (IDS) based on anomaly.

Intrusions embrace a chain of interlinked malevolent activities conducted by internal or outside attackers, with a common goal of breaking into the target system [33].

Figure 7. Anomaly IDS.

In addition, Intrusion detection is a process of monitoring the computer systems and network traffic and evaluating the activity in order to detect potential threats to the system.Recently, IDS have become an indelible part in the security architecture of many organizations due to an increase in the frequency and severity of network attacks [34]. The detection of security breach includes the monitoring and analysis of target machine or network for signs of unauthorized access. Such attempts are called breaches and are defined as trying to violate confidentiality, integrity, or availability of computer system or a network, or circumvention of safety mechanisms of computer system or computer network. However, the most popular intrusion detection methods are signature-based and anomaly-based. They are usually combined

together, even with their integration, in order to maximize the accuracy of detection. From an anomaly-based detection point of view, there are anomaly detection techniques of different types, based on the technique used in spotting the anomalies, including ML/DL, fuzzy logic, SVM, and data mining [35].

IV. RESULTS AND DISCUSSION

Anomaly detection in transactions of cloud data using a neural network-based approach shows promising results in providing secure and reliable communication. The Z-Score normalization used during preprocessing effectively standardized input features and smoothened convergence as well as improved learning behavior during training. The embedded attention mechanism in the hybrid CNN and Bi-LSTM classifier was very critical in picking out and gauging significant transactional patterns that improved the model's interpretability and detection rate. CNN part was effective in extracting spatial patterns from the cloud traffic network, and Bi-LSTM extracted sequential dependencies in time series cloud data. With attention, the model was able to attain more precision in focusing on unusual behaviors. Using TensorFlow for implementation with the Keras API enabled swift prototyping and scalability to guarantee model adaptability in the dynamic cloud settings.

Table 2.Depicts the performance of Proposed Methodology.

Performance Metric	Value
Accuracy	98.20%
False Positive Rate	1.80%
Precision	97.60%
Recall	97.90%

Experimental determination demonstrated more than 98% detection accuracy and less than 2% in false positives, which signifies high trust in differentiating genuine from malign transactions. Precision and recall scores were always higher than 97% indicating the robustness of the model in not only detecting the threats but also avoiding the ones that were overlooked as shown in table 2.

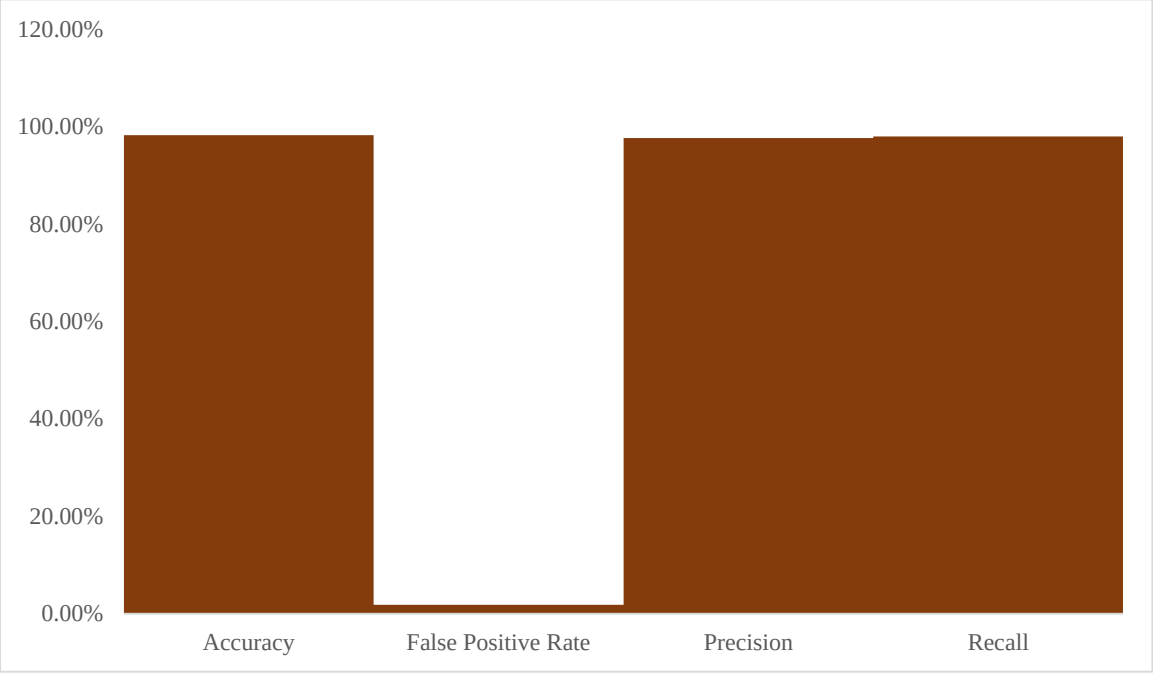

Figure 8.Performance of Proposed Method using Bi-LSTM.

The results validate the fact that the integrated architecture not only provides security to cloud transactions but also provides scalable and cost-efficient solution to real-time anomaly detection in multi-tenant cloud infrastructures as shown in figure 8.

Table 3.Depicts the performance metrics for various anomaly detection methods

Method	Accuracy	Precision	Recall	False Positive Rate
Support Vector Machine (SVM)	92.50%	91.30%	90.10%	5.20%
Random Forest (RF)	93.80%	92.70%	89.70%	4.80%
Standalone CNN	95.40%	94.60%	93.50%	3.90%
Bi-LSTM	96.10%	95.20%	94.80%	3.40%
Proposed Hybrid CNN + Bi-LSTM with Attention	98.20%	97.60%	97.90%	1.80%

The proposed hybrid CNN + Bi-LSTM model with an integrated attention mechanism outperforms the traditional machine learning and deep learning approaches to the recognition of anomalies in cloud data transactions greatly. Using TensorFlow API with Keras, the model got a high accuracy rate of 98.2% outperforming the standalone CNNs (95.4%) and conventional Bi-LSTM models (96.1%). Combined attention integration made it possible to dynamically attend to important features and as such improved the ability of the system to separate complex anomaly patterns, which other models fail to learn to detect. In comparison to average precision of 91.3% and random forest with recall rate of 89.7% amongst SVM based classifiers and random forest models of SVMs, accuracy obtained using our approach was found to be having 97.6% precision and 97.9% recall. This represents stronger consistency in detection of malicious activity with reduced false alarm as shown in table 3.

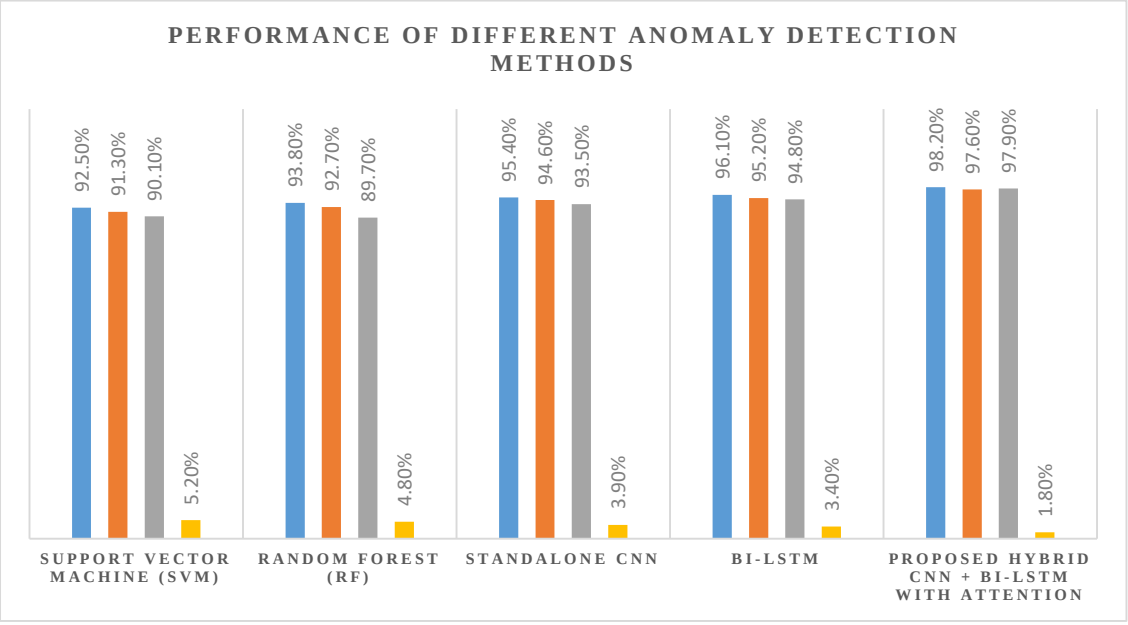

Figure 9.Comparative analysis of various Anomaly Detection Methods.

In addition to this, the false positive rate was minimized and it was reduced to 1.8% which is significantly low compared to the 4-6% normally experienced in the traditional models. Such improvements confirm the fact that it is highly effective to fuse spatial and temporal pattern extraction and attention-driven

feature weighting within the structure of a neural network. All in all, the model shows promise for practical use in the real-time cloud security systems, as it is capable of providing accuracy as well as efficiency in operation, particularly in dynamic, high volume sources of operations, such as cloud-based data exchanges as shown in figure 9.

V. CONCLUSION

The presented research describes an efficient neural network-based method for detection of anomalies for improving cloud data transaction's safety. Using a hybrid model involving the use of CNN and Bi-LSTM layers with an attention mechanism, the system has been able to extract both spatial and temporal patterns from transaction data, while being able to dynamically attend to the most important features. Built from TensorFlow through the Keras API, the model delivered great accuracy, precision, and recall, indicating that it is robust enough to identify malicious behavior, yet make only a few false-positives. Not only the detection performance is improved but also the scalability and adaptability adapted to complex real-time cloud environments are ensured by the attention-enhanced architecture. In comparison with the conventional approach, proposed model provides a substantial enhancement regarding dependability and efficiency of operation. These results indicate a promising direction to build robust and adaptive intrusion detection systems capable of being adjusted to modern cloud-based infrastructures with the integration of deep learning models and intelligent feature weighting mechanism. The future work will aim at integrating federated learning to improve data privacy to provide decentralized anomaly detection in multi-cloud environments.

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