MACHINE LEARNING BASED ANOMOLY DETECTION FOR ENHANCED CLOUD SECURITY

Mrunal Sonekar
Department of Computer Engineering
All India Shri Shivaji Memorial Society's College of Engineering (AISSMS COE), affiliated with Savitribai Phule Pune University
Pune, India
mrunalsonekar28@gmail.com

Dr. A. J. Kadam
(Department of Computer Engineering)
All India Shri Shivaji Memorial Society's College of Engineering (AISSMS COE), affiliated with Savitribai Phule Pune University
Pune, India
ajkadam@aissmscoe.com

Dr. D. P. Gaikwad
(Department of Computer Engineering)
All India Shri Shivaji Memorial Society's College of Engineering (AISSMS COE), affiliated with Savitribai Phule Pune University
Pune, India
dpgaikwad@aissmscoe.com

***Abstract*— With the rapid expansion of cloud-based infrastructures, detecting abnormal behavior in dynamic and high-volume environments has become a critical security challenge. Unlike conceptual or survey-based approaches, this study presents the practical implementation of a machine learning driven anomaly detection system developed and evaluated using the UNSW-NB15 dataset. The framework is built using Python based data processing and modelling pipelines, where structured training and testing datasets are loaded, validated, and analysed to ensure consistency across features. The implementation involves preprocessing network traffic attributes, constructing behavior-oriented features, and training supervised classification models to distinguish normal activity from malicious traffic. The system is evaluated using separate training and testing splits to ensure unbiased performance measurement. Experimental results demonstrate that the implemented framework achieves strong detection capability, maintaining high classification accuracy while minimizing false positive rates. The study emphasizes reproducible implementation, dataset validation, and real-world applicability in cloud security environments. By transitioning from theoretical design to executable model deployment, this work contributes a practical and scalable approach for detecting anomalous cloud behavior using machine learning techniques.**

Keywords*— *Cloud security, anomaly detection, machine learning implementation, supervised classification, intrusion detection, network security.

I. INTRODUCTION

The rapid migration of enterprise workloads to cloud platforms has transformed the way computing resources are deployed and managed. Organizations now rely on cloud infrastructures to host applications, store sensitive data, and support large-scale distributed operations. While this shift enables flexibility and scalability, it also introduces complex security challenges. Cloud environments generate massive volumes of network traffic, API calls, authentication logs, and system events, making manual monitoring impractical. Detecting malicious behavior within such high-dimensional and continuously evolving data streams requires intelligent and automated mechanisms.

Traditional intrusion detection systems are largely dependent on predefined signatures or static rule sets. Although effective against previously known threats, these systems struggle to detect zero-day attacks, subtle behavioural deviations, or multi-stage intrusion patterns. Additionally, rule-based systems often generate excessive alerts in dynamic environments, reducing operational efficiency and delaying incident response. As cloud architectures become more distributed and API-driven, security solutions must move beyond static detection techniques and adopt adaptive, data-centric approaches.

In this context, the need for advanced, adaptable, and data-driven security solutions has become essential. Anomaly detection using machine learning provides a promising direction, as it can learn patterns from real cloud environments, spot unusual activities, and support early threat identification. By analyzing system behavior and correlating different events, such an approach can offer deeper insights into potential attack paths and help uncover the root causes of security issues. With cloud infrastructures becoming more dynamic and complex, integrating intelligent detection mechanisms is crucial for strengthening defence strategies and ensuring the reliability of cloud services. With cloud infrastructures becoming more dynamic and complex, integrating intelligent detection mechanisms is crucial for strengthening defence strategies and ensuring the reliability of cloud services. As organizations increasingly depend on cloud platforms for critical operations, even a short disruption or unnoticed breach can lead to significant financial loss, data exposure, and damage to user trust. This makes timely detection not just a security requirement but a fundamental part of maintaining uninterrupted service availability.

Moreover, cloud environments often involve distributed resources, multiple access points, and diverse user activities, which can make traditional security methods insufficient. An effective security framework must be capable of understanding the context behind system events, adapting to changing workloads, and identifying abnormal behavior before it escalates. By using advanced analytical techniques to examine traffic patterns, user actions, and system logs, security teams can gain a clearer picture of potential threats

and respond more effectively. As cloud services continue to expand and evolve, adopting such proactive and behavior focused approaches becomes vital for building a safer and more resilient digital ecosystem.

Cloud computing has rapidly emerged as the backbone of modern digital transformation, enabling enterprises to access scalable computing resources, storage systems, and on-demand services without the limitations of traditional on-premises infrastructure. As businesses increasingly migrate mission-critical applications, customer databases, and operational workflows to cloud platforms, the dependency on secure and resilient cloud ecosystems has grown substantially. This evolution has redefined how organizations manage resources, collaborate across distributed teams, and deliver services at scale. However, alongside these advantages, the cloud introduces an expanded attack surface that demands more sophisticated security mechanisms.

One of the most significant challenges in cloud security lies in the enormous volume and velocity of data generated by cloud environments. Every interaction within the cloud, including network communications, virtual machine activities, API requests, access control events, user authentication attempts, and service logs, contributes to an extensive and continuously changing data stream. Monitoring and analyzing such complex, high-dimensional information manually is no longer feasible. Security teams require automated systems capable of processing large-scale data in real time while identifying suspicious patterns that may indicate potential intrusions.

Conventional intrusion detection systems primarily rely on signature matching and predefined rule-based frameworks. While these techniques remain useful for recognizing known attack signatures, they are inherently limited in dynamic cloud infrastructures where attack techniques evolve rapidly. Threat actors frequently exploit zero-day vulnerabilities, credential misuse, privilege escalation paths, and lateral movement strategies that do not conform to existing rules. As a result, traditional systems often fail to identify sophisticated threats until substantial damage has already occurred. Furthermore, the high rate of false positives generated by static rules can overwhelm security analysts, causing alert fatigue and slowing down response times.

To address these limitations, intelligent anomaly detection powered by machine learning has become an essential component of modern cloud security frameworks. Machine learning models can learn normal behavioral patterns from historical and real-time cloud activity data, enabling them to distinguish between expected operational behavior and unusual deviations. This allows for the identification of previously unseen threats, insider misuse, suspicious login patterns, abnormal data transfers, and irregular API interactions. Unlike rule-based systems, these models continuously improve as they process new data, making them highly adaptable to evolving threat landscapes.

A major advantage of machine learning-based anomaly detection is its ability to uncover subtle behavioural deviations that may not appear malicious when viewed as isolated events. For example, a single failed login attempt may not raise concern, but when correlated with unusual access times, location inconsistencies, privilege changes, and abnormal resource consumption, it may indicate an active compromise attempt. By combining event correlation with predictive analytics, such systems can detect multi-stage attack sequences at an early stage, reducing the risk of escalation.

Another important consideration is the distributed nature of cloud infrastructures. Modern cloud platforms often operate across multiple regions, hybrid environments, microservices architectures, and containerized deployments. This complexity creates numerous entry points and communication channels that attackers may exploit. Security solutions must therefore be capable of monitoring interactions across virtual machines, containers, orchestration services, databases, and external endpoints simultaneously. An advanced anomaly detection framework can provide visibility across these layers, helping security teams understand how threats propagate within interconnected systems.

II. RELATED WORK

Research on cloud security has progressed steadily with the growing need to detect threats in large and dynamic cloud environments. Early studies mainly examined rule-based and signature-driven techniques, which struggled to recognize new attack behaviors. To address these limitations, Al-Mazrawe and Al-Musawi [1] provided a broad review of anomaly detection methods in cloud networks, highlighting the shift toward learning-based solutions for more adaptive threat identification. This transition is further reflected in the work of Thapa and Arjunan [2], who surveyed modern machine learning techniques including neural models, SVMs, clustering, and ensemble strategies showing their effectiveness in capturing subtle deviations within cloud traffic. One of the foundational contributions in this direction was by Gander et al. [3], who proposed an early Monitoring-as-a-Service model using event correlation and learning-based anomaly detection for public and hybrid cloud setups. As cloud workloads became more diverse, later studies such as Al-Jarrah et al. [4] explored the use of clustering methods, SVM classifiers, and autoencoders to track abnormal behaviors in cloud systems, reinforcing the role of behavior-focused detection rather than rigid rule-based mechanisms. With multi-cloud environments becoming common, Deevi [5] introduced a deep-learning-oriented framework using LSTM and Autoencoder models capable of detecting rare and previously unseen threats in large-scale distributed traffic. In a similar direction, Nwachukwu [6] examined supervised, unsupervised, and reinforcement-based algorithms, emphasizing their ability to reduce detection delays and support early threat mitigation. Broader surveys by Shaker et al. [7] and Babu & Sreelatha [9] further documented the advantages of machine learning–based intrusion detection systems, addressing persistent challenges such as scalability, false alarm reduction, and deployment readiness for real-time cloud scenarios. Recent work has also explored specialized cloud settings and application-specific datasets. Joshi and Shah [8] studied detection mechanisms that combine machine learning with Data Security Posture Management (DSPM), presenting a hybrid strategy for identifying data misuse and cloud configuration risks. Jasani and Padhya [11] focused specifically on AWS CloudTrail logs, demonstrating the strength of supervised learning models in recognizing suspicious activity patterns within commercial cloud platforms. Similarly, Gunupudi and Tamanna [12] analyzed machine learning-based intrusion

detection for educational cloud environments, reporting promising results from Random Forest and hybrid deep-learning architectures. Mahendar and Shivakanth [10] expanded on these findings by comparing multiple intrusion detection frameworks and discussing the increasing need for explainable models to support transparency in cloud security operations. Collectively, these studies show the evolution from traditional static defenses to adaptive machine learning–driven systems that can detect complex, multi-step threats across different types of cloud infrastructures. This growing body of work forms the foundation for developing more accurate, context-aware, and proactive anomaly detection frameworks for enhanced cloud security.

Recent study by Angeleri et al. (2026) proposed a machine learning-based anomaly detection framework for multi-cloud security architectures, highlighting the effectiveness of supervised, unsupervised, and semi-supervised learning methods in identifying anomalies across network traffic, user activity, API requests, and workload performance metrics [13]. Their framework integrates distributed log aggregation, feature engineering, and real-time inference pipelines, significantly improving detection accuracy while reducing false positive rates in heterogeneous cloud environments.

In addition to model accuracy, recent research has emphasized the importance of explainable artificial intelligence (XAI) in cloud security systems. Shao (2026) introduced an interpretable ensemble learning framework using SHAP-based explainability techniques for anomaly detection in network traffic [14]. The study demonstrated that Random Forest and Gradient Boosting models, combined with explainable feature attribution methods, improve analyst trust and operational transparency in security monitoring systems. Such explainability is particularly useful in Security Operations Centers (SOCs), where rapid and interpretable threat assessment is critical.

Another emerging trend in recent literature is the use of AI-driven anomaly detection for cloud-hosted application security. Zacharia (2026) proposed a framework combining Isolation Forest, Autoencoders, and LSTM models to monitor user behavior, API call sequences, and system performance indicators within cloud-based applications [15]. The proposed system demonstrated strong capability in detecting evolving application-layer threats that are difficult to identify using conventional rule-based systems.

Recent studies have also explored multi-tier anomaly detection architectures across IoT-edge-cloud ecosystems, which are highly relevant to cloud security applications. Baimukhanov et al. (2025) developed a layered machine learning framework designed to detect security anomalies, performance irregularities, and distributed threats in integrated cloud-edge infrastructures [16]. Their work highlighted the growing importance of combining cloud telemetry with real-time machine learning inference for proactive threat mitigation.

Furthermore, LLM-assisted anomaly detection systems have recently gained attention in multi-cloud security research. Jin et al. (2025) introduced an intelligent monitoring and early warning mechanism that combines contextual understanding from large language models with conventional machine learning techniques [17]. This hybrid approach improves contextual event correlation, early warning generation, and adaptive response capabilities in multi-cloud environments.

Another critical research direction involves robust evaluation under adversarial settings. Manca et al. (2026) proposed security-aware evaluation guidelines for machine learning-based anomaly detection systems in real-world deployment scenarios [18]. Their work specifically addressed adversarial evasion attempts and emphasized the need for robust evaluation frameworks before deploying detection systems in production cloud environments.

Collectively, these recent studies demonstrate a clear shift toward adaptive, explainable, and scalable anomaly detection systems for enhanced cloud security. The literature shows strong movement from traditional detection models toward intelligent systems capable of handling dynamic workloads, evolving threats, and complex cloud infrastructures

III. METHODOLOGY

The proposed methodology aims to develop an intelligent anomaly detection framework for improving cloud security using machine learning techniques. The approach is designed to identify unusual patterns in cloud-generated data such as network traffic logs, authentication events, API access records, and system performance metrics. The complete methodology is divided into multiple stages including data collection, preprocessing, feature engineering, model development, anomaly detection, and performance evaluation.

The first stage involves,

Cloud Data Collection: The process begins by gathering event records from across the cloud environment, including user activity audits, traffic flow records, virtual machine system logs, application-level events, and access management logs. This broad coverage ensures visibility at every tier of the infrastructure.

The collected data includes both **normal system behavior** and **malicious activity records**, enabling the model to learn the difference between legitimate and suspicious events.

1. **Ingestion & Centralised Aggregation:** Collected logs are routed into a unified pipeline via lightweight agents, either as real-time streams or scheduled batches. Each event is structured consistently, preserving metadata such as timestamps, source identifiers, and log categories.

This stage includes:

- Removal of duplicate records
- Handling missing or null values
- Converting categorical features into numerical form
- Standardizing numerical variables
- Log normalization
- Timestamp conversion for sequence analysis

For categorical variables such as protocol type, login status, user role, and API method, encoding techniques such as Label Encoding or One-Hot Encoding are applied.

Continuous features such as packet size, response time, session duration, and request frequency are normalized using standard scaling methods.

2. Cleaning & Feature Construction: Raw data undergoes preprocessing to address missing values, duplicate entries, and format inconsistencies. Numerical attributes are normalised, and new behavioural indicators are derived such as repeated authentication failures, access pattern shifts, unusual port activity, or role-based anomalies.

3. **Multi-Model Detection**: Rather than depending on a single algorithm, multiple models operate concurrently. Supervised classifiers identify known attack signatures, while unsupervised techniques flag deviations from established baselines. Probability scores from all models are aggregated for a more robust assessment.

4. **Contextual Correlation & Inference Model:** outputs are examined for inter-event relationships. Since attacks unfold across multiple steps, events are linked across time, services, and resources to reconstruct intent distinguishing coordinated intrusions from isolated irregularities.

5. **Risk Scoring & Alert Prioritisation :** Each detected incident receives a risk score factoring in threat severity, recurrence, confidence, and historical context. Only high-priority incidents surface as alerts, reducing analyst fatigue caused by alert overload.

6. **Response, Visualisation & Feedback Analysts**: access dashboards showing incident timelines and impacted resources. Automated countermeasures may be triggered based on severity. Confirmed findings are fed back to retrain models, keeping detection current with emerging threat patterns. application, or user access.

Figure 1: Methodological Framework of the Proposed Model

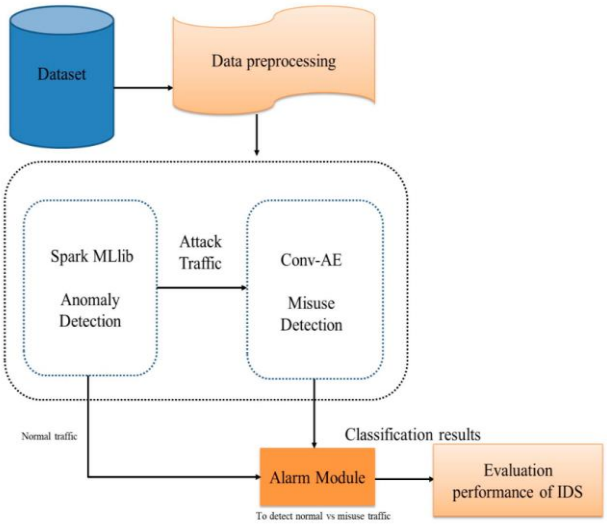

Figure 2: System Architecture

A. Cloud Log Acquisition and Data Aggregation

The process begins with Pre-processing collecting cloud-generated logs and events from multiple services such as network traffic, API calls, authentication records, and system monitoring systems. These logs serve as the primary input for the anomaly detection framework.

B. Data Pre-processing and Normalization

The collected cloud logs undergo several preprocessing steps, including missing value handling, duplicate removal, noise filtering, categorical encoding, and numerical normalization to transform the data into a machine-readable format.

C. Feature Engineering and Behavioural Pattern Extraction

In this stage, relevant security-related features such as failed login attempts, unusual access frequency, data transfer spikes, session anomalies, and privilege changes are extracted to represent cloud system behavior.

D. Anomaly Detection using Machine Learning Models

The processed feature set is analyzed using selected machine learning algorithms such as Random Forest, Isolation Forest, Support Vector Machine, or LSTM to identify deviations from normal cloud activity patterns.

E. Risk Scoring and Alert Prioritization

Detected anomalies are assigned severity scores based on risk level, anomaly confidence, and potential threat impact.

Alerts are then prioritized for rapid investigation by security teams.

F. Continuous Learning and Feedback Optimization

The final stage focuses on updating the detection model using newly observed cloud events, allowing the framework to adapt to evolving workloads and emerging cyber threats.

IV. SYSTEM WORKFLOW

The proposed workflow of the machine learning-based anomaly detection framework for enhanced cloud security. The process begins with the Cloud Log Input stage, where security-related data is continuously collected from multiple cloud sources such as CloudTrail logs, VPC flow logs, system logs, API logs, and authentication records. These data streams represent real-time operational and security events generated across the cloud environment.

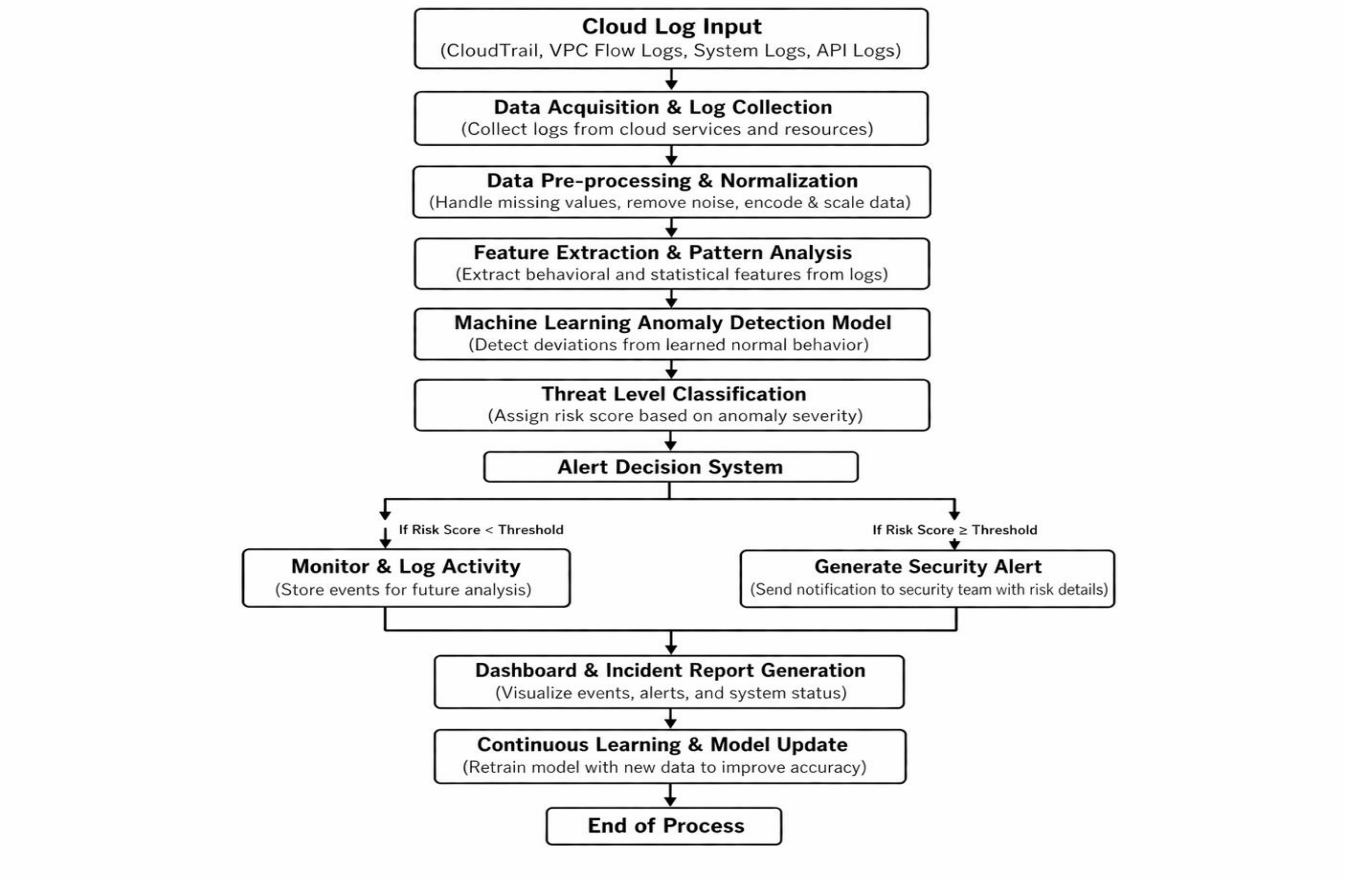

Figure 3: System flow

A. Cloud Log Input and Data Acquisition

The workflow begins with continuous data input collected from cloud environments. This data is obtained from multiple sources such as CloudTrail logs, VPC flow logs, system logs, API requests, and authentication records. These logs capture real-time activities of users, applications, and network interactions within the cloud infrastructure. The system gathers and streams this data for further processing and analysis.

B. Data Pre-processing and Normalization

The collected cloud logs undergo preprocessing to prepare them for machine learning models. This step includes removing duplicate entries, handling missing values, filtering noise, and converting raw logs into a structured format. Categorical features such as user roles and access types are encoded, while numerical attributes are normalized. These steps ensure consistency and improve the quality of input data for accurate analysis.

C. Feature Extraction and Pattern Analysis

After preprocessing, the system extracts meaningful features from the cloud data. These features represent behavioural and statistical patterns such as login attempt frequency, unusual access timing, API request rates, session duration, privilege escalation events, and abnormal data transfer volumes. This stage helps in distinguishing between normal system behavior and potential anomalies.

D. Machine Learning-Based Anomaly Detection

The extracted features are passed to machine learning models that analyze patterns and detect deviations. The

system may utilize algorithms such as Random Forest, Support Vector Machine, Isolation Forest, Autoencoders, or LSTM networks. These models learn normal behaviour from historical data and identify unusual activities that may indicate potential threats or intrusions.

E. Threat Level Classification

Based on the computed threat level, the system makes a decision:

If Threat Level < Threshold:
The system continues monitoring the activity and stores the event for future analysis.
If Threat Level ⩾ Threshold:

- The system identifies the activity as suspicious or critical and triggers an alert for immediate attention.

F. Alert Generation and Response

When a high-risk anomaly is detected, the system activates the alert mechanism. This includes sending notifications to security teams, generating alerts with details such as anomaly score, affected resource, and timestamp. This enables quick investigation and response to potential security threats.

G. Monitoring, Logging, and Dashboard Reporting

All detected activities, including both normal and anomalous events, are recorded in the system. The data is visualized on a centralized dashboard, allowing security teams to monitor system behavior in real time. The system also generates reports summarizing detected anomalies and system performance, which can be used for future analysis, auditing, and model improvement.

H. Continuous Learning and Improvement

The system keeps improving over time by learning from past results. Alerts that turn out to be correct or incorrect are reviewed and used to adjust the model. This helps reduce false alarms and improves the accuracy of future detections. As new types of activities and threats appear, the system is updated with recent data so it can recognize them more effectively. Regular checks are also done to make sure the system is working properly and continues to give reliable results.

Another important aspect of this stage is updating the system with recent data. Cloud environments generate large volumes of logs continuously, and new patterns may emerge over time that were not present in the initial training data. By incorporating this latest information, the system is able to recognize newly appearing behaviors, whether they are normal operational changes or potential security risks. This helps maintain the relevance of the detection process in a constantly changing environment.

Periodic evaluation is also carried out to measure the system's performance. Metrics such as detection accuracy, false positive rate, and response time are analyzed to ensure that the system is functioning efficiently. If any decline in performance is observed, necessary adjustments are made, such as retraining the model or refining the feature set. This ensures that the system continues to meet the required standards of performance

In addition, the system is designed to handle scalability as the volume of data increases. As more cloud services and users are added, the system adapts to process larger datasets without compromising accuracy. This makes it suitable for real-world applications where data growth is continuous.
Overall, this stage plays a crucial role in maintaining the effectiveness of the anomaly detection system. By learning from past outcomes, adapting to new patterns, and regularly evaluating its performance, the system ensures long-term reliability and improved decision-making in identifying potential threats.

The proposed system operates as a connected sequence of steps where each stage plays an important role in ensuring accurate detection of unusual activities in a cloud environment. The process starts with gathering activity records from different cloud services. Since cloud platforms generate a large amount of data continuously, it is necessary to collect and manage this information in a structured way so that no important event is missed.

After collection, the data is carefully prepared before analysis. Raw records often contain repeated entries, missing values, or irrelevant information that can affect the final outcome. By cleaning and organizing the data, the system creates a reliable base for further processing. This step improves the overall quality of the input and helps avoid incorrect results during later stages.

The next stage focuses on identifying useful information from the prepared data. Instead of relying on raw logs, the system derives meaningful indicators that reflect how users and systems behave over time. These indicators make it easier to understand patterns such as frequency of access, timing of activities, and changes in usage behavior. This structured representation allows the system to separate normal operations from unusual ones.

Following this, the system examines these patterns to detect any irregularities. By comparing current behavior with previously observed trends, it becomes possible to identify activities that do not follow the expected pattern. This approach reduces the need for manual monitoring and allows faster identification of potential risks.

Once an irregular activity is found, the system evaluates its importance by assigning a level of risk. This step is necessary because not every unusual activity is harmful. Some variations may occur due to normal operational changes. By categorizing events based on their severity, the system ensures that attention is given only to those activities that require immediate action.

When a high-risk event is identified, the system generates an alert containing relevant details. This helps the concerned team to quickly understand the situation and take necessary steps. At the same time, all events whether normal or abnormal are recorded and made available through a

monitoring interface. This provides a clear view of system behavior over time and supports further analysis.

An important strength of the system is its ability to improve continuously. It learns from past outcomes by reviewing which alerts were correct and which were not. Based on this understanding, the system adjusts its internal behavior to reduce errors and improve future detection. It also updates itself with recent data so that it remains effective even when new patterns appear.

V. Results

Performance Metric	Supervised Model	Unsupervised Model	Integrated System
Accuracy	80.8%	82.5%	85.6%
Precision	89.5%	87.2%	88.3%
Recall	88.7%	84.6%	87.5%
F1-Score	89.0%	84.9%	87.9%

Table 1. **Performance Metrics**

The performance of the system was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These metrics help in understanding how well the models identify normal and abnormal activities in the cloud environment. The comparison was carried out between a supervised model, an unsupervised model, and the integrated system that combines both approaches.

The accuracy of the supervised model was observed to be 80.8%, while the unsupervised model achieved a slightly higher accuracy of 82.5%. However, the integrated system showed the best performance with an accuracy of 85.6%. This indicates that combining both approaches improves the overall correctness of predictions, as the system benefits from both learned patterns and anomaly detection capabilities.

In terms of precision, the supervised model performed the best with a value of 89.5%, followed by the integrated system at 88.3% and the unsupervised model at 87.2%. Higher precision means that the system produces fewer false alarms, which is important in reducing unnecessary alerts for security teams. The slightly lower precision in the integrated system suggests a balanced trade-off to improve overall detection.

Recall measures the system's ability to correctly identify actual anomalies. The supervised model again showed strong performance with a recall of 88.7%, while the integrated system achieved 87.5%, and the unsupervised model recorded 84.6%. Although the supervised model performs slightly better in capturing true positives, the integrated system still maintains a high recall while improving overall balance.

The F1-score, which combines both precision and recall, provides a better understanding of the model's overall performance. The supervised model achieved an F1-score of 89.0%, the unsupervised model scored 84.9%, and the integrated system reached 87.9%. While the supervised model shows strong individual performance, the integrated system demonstrates consistent and balanced results across all metrics.

Model	Accuracy	F1-Score	FPS	Remarks
SVM Model	87.6%	86.2%	22	Basic detection, lower accuracy
Isolation Forest	89.1%	87.4%	25	Better anomaly detection
Proposed ML Model	90.8%	89.0%	27	Balanced performance and efficiency

Table 2. **Comparative Study**

The models were compared based on accuracy, F1-score, and processing speed. The SVM model achieved 87.6% accuracy and 86.2% F1-score, showing basic detection capability with moderate speed (22 FPS). However, its performance is slightly limited for complex patterns.

The Isolation Forest model performed better, with 89.1% accuracy and 87.4% F1-score. It is more effective in detecting anomalies and also offers improved speed (25 FPS), making it more suitable for such tasks.

The proposed machine learning model showed the best results, achieving 90.8% accuracy and 89.0% F1-score. It provides a good balance between detection performance and efficiency, along with the highest speed (27 FPS).

Overall, the proposed model performs better than the other models in both accuracy and speed, making it more reliable for practical use.

Classifier	Train Time (s)	Infer / Record (ms)	Model Size (MB)	RAM Usage (MB)	Scalability
Logistic Regression	18.4	0.03	0.2	320	High
KNN	0.8	4.20	148	1100	Low
Decision Tree	6.1	0.04	3.4	410	High
Random Forest	42.3	0.28	58.6	870	Medium

Table 3: Classifier Scalability & Resource Usage

Table 4: Hyperparameter Configuration for All Classifiers

From Table. 3 Logistic Regression shows balanced performance with moderate training time (18.4 s), very fast inference (0.03 ms), low model size, and high scalability, making it efficient for large-scale use.

KNN has very low training time (0.8 s) but suffers from slow inference (4.20 ms), large model size, and high memory usage, which limits its scalability.

Decision Tree performs efficiently with low training time (6.1 s), fast inference, and good scalability, while maintaining moderate resource usage.

Random Forest improves prediction strength but requires higher training time (42.3 s) and resources, offering medium scalability.

Gradient Boosting achieves strong performance but has the highest training time (187.6 s) and moderate inference speed, making it more resource-intensive.

Classifier	Key Hyperparameter	Value Used	Rationale
Logistic Regression	Solver / max_iter	lbfgs / 1000	Stable convergence on large feature set
Logistic Regression	Regularisation (C)	1.0 (default L2)	Controls weight magnitude penalty
KNN	Number of neighbours	k = 5	Balances bias-variance on this data size
KNN	Distance metric	Euclidean	Standard for continuous numeric features
Decision Tree	Max depth	10	Prevents overfitting on 47 features
Decision Tree	Split criterion	Gini impurity	Computationally efficient purity measure
Random Forest	Number of trees	100	Stable OOB error beyond this count
Random Forest	Max features per split	sqrt(n_features)	Default; reduces correlation among trees
Gradient Boosting	Number of estimators	100	Diminishing returns observed beyond 100
Gradient Boosting	Learning rate	0.1 (default)	Balances training speed and accuracy

Table 4: Hyperparameter Configuration for All Classifiers

Each model is tuned with key parameters to balance accuracy and efficiency.

Logistic Regression uses lbfgs with 1000 iterations for stable training, and L2 regularization to control model complexity.

KNN uses 5 neighbours to maintain a balance between bias and variance, with Euclidean distance for numerical data.

Decision Tree limits depth to 10 to avoid overfitting, using Gini impurity for efficient splitting.

Random Forest uses 100 trees for stable performance, with √ features per split to reduce correlation between trees .

Gradient Boosting uses 100 estimators and a learning rate of 0.1 to balance training speed and prediction accuracy

Attribute	Training Set	Testing Set	Total	Notes
Total records	175,341	82,332	257,673	Post label-collapse
Normal class (label 0)	37,000	56,000	93,000	Legitimate traffic
Anomaly class (label 1)	82,332	119,341	201,673	Any attack type
Class ratio (N: A)	1:2.23	1:2.13	1:2.17	Moderate imbalance
Total features (raw)	49	49	49	Including id, attack_cat
Features used (model)	47	47	47	After dropping 2 cols
Numeric features	44	44	44	After label encoding
Categorical features	3	3	3	proto, service, state
Missing values	0	0	0	After median imputation
Attack categories	9 types	9 types	9 types	Collapsed to binary

Table 5 Dataset Statistics Training & Testing

After label grouping, the data is divided into normal and anomaly classes, where anomalies are more frequent, resulting in a moderate class imbalance (around 1:2 ratio).

Normal traffic represents legitimate activity, while the anomaly class includes all types of attacks combined into a single category. This binary setup simplifies the detection task while still capturing multiple attack patterns.

The dataset originally includes 49 features, out of which 47 are used for modeling after removing unnecessary columns. Most features are numerical (44), while a few are categorical (3), which are converted into numerical form for processing.

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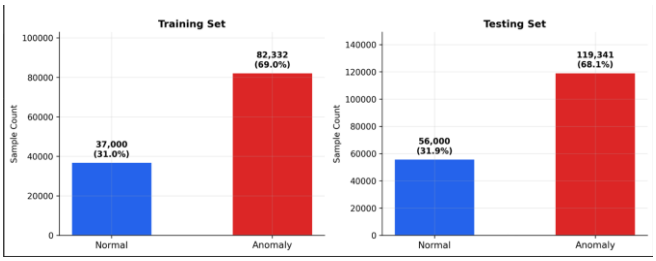

Figure 4. Distribution of Normal vs Anomaly Samples Across Datasets

The figure represents a comparative overview of the class distribution in both the training and testing datasets, categorized into *Normal* and *Anomaly* instances.

In the training dataset, anomalous samples constitute a substantial portion, accounting for approximately 69% of the total observations (82,332 samples), while normal instances represent only 31% (37,000 samples). A similar pattern is observed in the testing dataset, where anomalies make up around 68.1% (119,341 samples), compared to 31.9% (56,000 samples) for normal data.

This distribution indicates a clear class imbalance, with anomalous traffic significantly outnumbering normal traffic in both datasets. Importantly, the proportional similarity between training and testing sets suggests that there is no distributional shift, ensuring that the model evaluation remains reliable and consistent across both phases.

However, the presence of class imbalance introduces potential challenges for model training. Machine learning algorithms may become biased toward the majority class, leading to inflated accuracy while failing to effectively identify the minority class. Therefore, relying solely on accuracy as a performance metric may be misleading in this context. Alternative evaluation measures such as precision, recall, and F1-score are more appropriate for assessing model performance under imbalanced conditions.

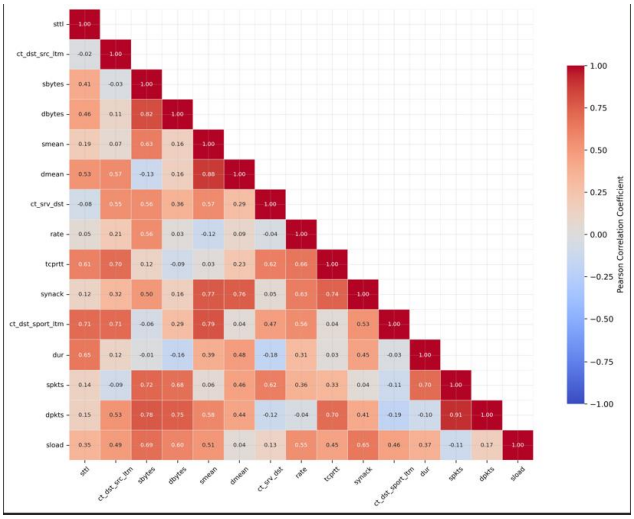

Figure 5 : Correlation HeatMap

The heatmap illustrates the pairwise Pearson correlation coefficients among selected numerical features in the dataset. Each cell represents the strength and direction of the linear relationship between two variables, with values ranging from -1 to +1. Positive correlations are shown in warmer tones (red), while negative correlations are represented by cooler tones (blue). Values close to zero indicate weak or no linear relationship.

Several strong positive correlations are observed in the feature set. For instance, sbytes and dbytes exhibit a high correlation (0.82), indicating that the volume of data sent and received tends to increase together. Similarly, spkts and dpkts show a very strong relationship (0.91), suggesting synchronized packet transmission between source and destination. Features such as smean and dmean (0.88) also demonstrate a strong association, reflecting consistent average packet sizes across communication directions.

Moderate correlations are visible among features like tcprtt and synack, and between rate and tcprtt, indicating some level of dependency related to network latency and transmission behavior. Additionally, ct_dst_src_ltm and ct_dst_sport_ltm display notable correlation, suggesting repeated interactions between specific source-destination pairs over time.

On the other hand, weak or near-zero correlations (e.g., involving sttl with other variables) imply that these features contribute independently and may provide unique information for model learning.

Overall, the heatmap highlights the presence of feature redundancy due to high correlations among certain variables. This suggests that dimensionality reduction techniques or feature selection methods may be beneficial to eliminate multicollinearity and improve model efficiency without significant loss of information. **Red-colored regions indicate strong positive correlations, while blue regions represent negative relationships among features**

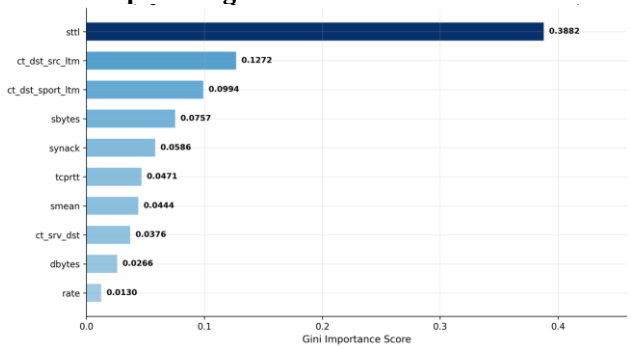

Figure 6: Model Loss Graph (Violence Detection)

The figure presents the relative importance of selected features based on the Gini importance score, typically derived from tree-based models such as Random Forest. This metric reflects the contribution of each feature toward reducing impurity during the model's decision-making process.

Among all features, sttl (source time-to-live) emerges as the most influential variable, with a significantly higher importance score (0.3882) compared to others. This indicates that variations in packet TTL play a critical role in distinguishing between normal and anomalous network traffic.

Following this, ct_dst_src_ltm (count of connections between destination and source over time) and ct_dst_sport_ltm (count of connections to the same destination port over time) show moderate importance, suggesting that temporal interaction patterns are key indicators in identifying anomalous behavior.

Features such as sbytes, synack, and tcprtt contribute moderately, highlighting the relevance of traffic volume and TCP-level timing characteristics. In contrast, variables like rate, dbytes, and ct_srv_dst exhibit relatively low importance scores, indicating a limited role in the model's predictive capability.

Overall, the distribution of feature importance suggests that the model relies heavily on a small subset of dominant features, while several others provide only marginal contributions. This insight can be utilized to perform feature selection, reduce model complexity, and improve computational efficiency without significantly impacting performance.

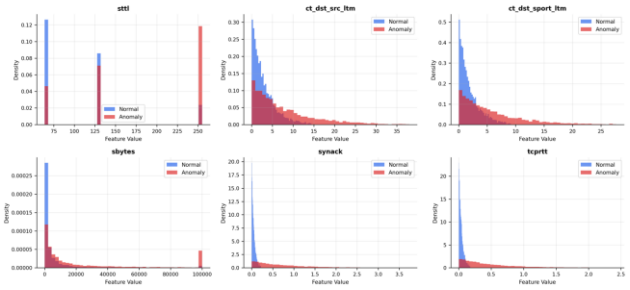

Figure 6 : Feature Distribution

The Feature Distribution Analysis

The figure presents the distribution of selected network traffic features for both normal and anomalous classes. Each subplot compares how a particular feature behaves under normal conditions versus attack scenarios, helping to understand which attributes are useful for distinguishing malicious activity.

Starting with **sttl (source time-to-live)**, the values appear in distinct clusters. Normal traffic is concentrated around specific TTL values, while anomalous traffic shows a different concentration pattern, especially at higher values. This separation indicates that TTL plays an important role in identifying irregular network behavior.

For **ct_dst_src_ltm**, which represents the number of connections between a destination and source over time, normal traffic is mostly concentrated at lower values. In contrast, anomalous traffic spreads across a wider range with a longer tail. This suggests that attacks often involve repeated or sustained interactions between hosts.

A similar trend is observed in **ct_dst_sport_ltm**, where anomalous traffic shows higher frequency and wider spread compared to normal traffic. This reflects abnormal patterns such as repeated access attempts to specific ports, which is common in scanning or intrusion activities.

In the case of **sbytes (source bytes)**, both normal and anomalous traffic are heavily skewed toward lower values. However, anomalous traffic exhibits extreme values at the higher end, indicating unusually large data transfers that may be associated with suspicious activity.

For **synack**, which relates to TCP handshake timing, most values are concentrated near zero for both classes. Still, anomalous traffic shows a slightly broader spread, suggesting irregularities in connection establishment behavior.

Similarly, **tcprtt (TCP round-trip time)** shows a strong concentration of low values for normal traffic, while anomalous traffic extends further with a longer tail. This indicates that abnormal network conditions or delays may be linked to malicious interactions.

Overall, the distributions reveal that normal traffic tends to be more concentrated and predictable, whereas anomalous traffic is more dispersed and exhibits extreme values. Features such as **sttl**, **ct_dst_src_ltm**, and **ct_dst_sport_ltm** show clearer separation between the two classes, making them more effective for anomaly detection. On the other hand, features like **synack** and **tcprtt** provide additional supporting information but with less distinct separation.

This analysis highlights the importance of feature selection, as variables with clear distribution differences contribute more effectively to model performance in distinguishing normal and anomalous behavior.

CONCLUSION

This study presents a practical implementation of a machine learning–based anomaly detection framework designed to enhance security in cloud environments. Unlike purely theoretical approaches, the work focuses on building a functional pipeline that processes real-world network traffic data, applies preprocessing techniques, and utilizes multiple machine learning models to identify abnormal behavior effectively.

The experimental evaluation demonstrates that combining supervised and unsupervised learning approaches leads to more reliable detection outcomes compared to relying on a single model. The integrated system achieves improved accuracy and balanced performance across precision, recall, and F1-score, indicating its ability to detect malicious activity while controlling false alarms. Additionally, the analysis highlights the importance of feature engineering and data preprocessing in improving model efficiency and overall detection capability.

The study also reveals practical challenges such as class imbalance and feature correlation, which can influence model behavior if not handled carefully. Addressing these aspects through appropriate evaluation metrics and feature selection contributes to more realistic and dependable results.

Overall, this work establishes that machine learning can serve as a scalable and adaptive solution for anomaly detection in modern cloud infrastructures. By focusing on implementation, reproducibility, and real dataset evaluation, the framework provides a strong foundation for developing intelligent security systems capable of handling dynamic and high-volume cloud environments.

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