FAULT DETECTION IN CLOUD COMPUTING USING DECISION TREE ALGORITHM

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APPROVAL PAGE

This is to certify that this project was carried out by **OLAITAN TAOFEEK AYOMIDE** with Matric Number: **ND/23/COM/PT/0314** has been read and approved by the Department of Computer Science, Kwara State Polytechnic Ilorin. In partial fulfillment of the requirements for the award of National Diploma (ND) in Computer Science.

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DEDICATION

This research project is dedicated to the Almighty God, the giver of life and taker of life that guide me throughout my program.

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All Glory and adoration belong to him alone (God), Omniscience, and Omnipresent for his mercy over me throughout my undergraduate journey, which of your favour I will deny absolutely none.

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Also, to the school management (Kwara State Polytechnic, Ilorin) and entire Staff of Computer Science Department, starting from the Head of Department in person of **Mr. Oyedepo, F.S,** I appreciate you all.

To all my friend and family, I can't be mention all of you, we shall all meet in the field of success.

Thank you all.

TABLE OF CONTENT

Abstract

The rapid adoption of cloud computing has significantly transformed how organizations manage data and resources, offering scalable, on-demand services across distributed infrastructures. However, the increasing complexity of these environments has led to challenges in maintaining reliability and performance, especially in detecting and responding to faults. Faults in cloud systems—ranging from hardware failures to network bottlenecks can disrupt service availability and degrade user experience. This research addresses the problem of fault detection in cloud computing using a Decision Tree algorithm, a supervised machine learning model known for its interpretability and low computational complexity. A synthetic dataset was constructed to simulate various cloud metrics such as CPU usage, memory load, disk I/O, latency, and error frequency. Preprocessing techniques including normalization and encoding were applied, and the model was trained and evaluated using Python libraries such as Scikit-learn. The Decision Tree classifier effectively categorized system states as "normal" or "faulty" with high accuracy, demonstrating its potential for real-time anomaly detection in cloud environments. Evaluation metrics such as confusion matrix, accuracy score, and classification report validated the model's reliability. The study concludes that the Decision Tree algorithm provides a viable and efficient solution for early fault detection in cloud computing, thereby supporting more resilient and self-managing infrastructures. Future work could explore real-time implementation and integration with other advanced learning techniques such as ensemble models or neural networks.

Keywords: Cloud Computing, Fault Detection, Decision Tree, Supervised Learning, Machine Learning, Cloud Reliability, Anomaly Detection, System Monitoring

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Cloud computing has revolutionized the landscape of modern information technology by providing scalable, flexible, and cost-efficient computing resources over the internet. It enables the delivery of computing services such as servers, storage, databases, networking, software, and analytics through platforms like Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP). As organizations increasingly migrate their operations to cloud environments, maintaining high availability and reliability becomes a critical concern. Faults—defined as any unexpected behavior that impairs the normal functioning of cloud-based systems—can lead to service disruptions, data loss, reduced performance, and increased operational costs. Therefore, robust and efficient fault detection mechanisms are imperative to uphold the service level agreements (SLAs) between cloud service providers and clients (Singh et al., 2022).

In the dynamic and complex nature of cloud infrastructures, faults may arise from various components such as hardware, software, network, and virtualization layers. These faults can be transient, intermittent, or permanent, each posing unique challenges for detection and resolution. Traditional fault detection approaches rely heavily on rule-based systems, log analysis, and threshold-based monitoring tools. While these techniques offer some level of reliability, they often fail to detect subtle or emerging anomalies and require manual intervention, making them inadequate for today’s large-scale, distributed cloud systems (Amin et al., 2023).

Furthermore, the volume of operational data generated by cloud infrastructures necessitates automated, intelligent systems capable of real-time analysis and proactive decision-making. In response to these challenges, the research community has increasingly turned to machine learning (ML) methods for fault detection and diagnosis in cloud computing environments. Machine learning models can learn from historical data, identify patterns, and make accurate predictions about potential faults without being explicitly programmed. Among various ML techniques, the Decision Tree algorithm has gained attention for its simplicity, interpretability, and effectiveness in classification tasks (Zhao & Kumar, 2023).

A Decision Tree uses a tree-like model of decisions and their possible consequences, enabling it to classify input features such as CPU usage, memory consumption, disk I/O, and network latency into fault or non-fault categories. Recent studies have demonstrated the promising performance of Decision Tree algorithms in fault detection systems. For instance, Qureshi et al. (2024) applied a Decision Tree-based model to detect hardware and software faults in virtualized cloud environments, achieving over 90% accuracy. Their findings suggest that Decision Trees not only provide high precision but are also suitable for real-time monitoring due to their low computational overhead. Similarly, Adegbite and Musa (2025) integrated Decision Tree classifiers into a hybrid fault management system, improving fault localization speed and reducing false positives in comparison to traditional methods. These advancements highlight the potential of Decision Tree models in enhancing the robustness and efficiency of cloud computing infrastructures.

However, while Decision Trees offer significant advantages, they are not without limitations. Overfitting, particularly when the tree becomes too deep, can reduce the model’s generalization ability. To address this, techniques such as pruning, cross-validation, and ensemble methods like

Random Forest and Gradient Boosting are often employed. Despite these limitations, Decision Trees remain a powerful tool for initial fault detection systems, especially when model transparency and interpretability are important (Fernández et al., 2023). This is particularly relevant in cloud environments, where administrators need clear explanations for automated decisions to take appropriate remedial actions.

The goal of this research is to develop a fault detection system using the Decision Tree algorithm tailored for cloud computing infrastructures. By analyzing real-world cloud system logs and operational data, the system aims to classify and predict faults efficiently. This approach not only supports early fault detection but also contributes to proactive fault management, minimizing system downtime and optimizing performance. The research aligns with the ongoing efforts to integrate intelligent systems into cloud management frameworks, enhancing their self-healing and autonomous capabilities.

In conclusion, this study proposes the implementation of a Decision Tree-based fault detection model as a viable solution to the limitations of traditional fault management techniques in cloud computing. Through effective classification of cloud system metrics, the proposed model aims to improve reliability, reduce downtime, and enable proactive fault handling in modern cloud environments. The research contributes to the growing body of knowledge in intelligent cloud management and supports the advancement of resilient computing infrastructures.

1.2 Statement of the Problem

Despite the numerous advantages offered by cloud computing, ensuring system reliability remains a significant challenge due to frequent and unpredictable faults occurring in various components such as servers, virtual machines, networks, and storage systems. Traditional fault detection mechanisms often rely on static threshold rules and manual monitoring, which are inadequate in handling the dynamic and complex nature of modern cloud infrastructures.

These conventional approaches are slow to respond, fail to detect emerging anomalies, and contribute to prolonged system downtimes, increased operational costs, and violated service level agreements (SLAs). Moreover, the sheer volume of data generated by cloud systems makes real-time fault detection difficult without intelligent automation. There is a pressing need for accurate, efficient, and interpretable fault detection models that can learn from historical data and make timely predictions. This research addresses this gap by proposing the use of the Decision Tree algorithm for effective and proactive fault detection in cloud computing environments.

1.3 Aim and Objectives of the Study

The aim of this study is to develop an intelligent fault detection system for cloud computing environments using the Decision Tree algorithm to enhance system reliability, minimize downtime, and support proactive fault management.

Objectives of the Study:

i. To examine the common causes and types of faults in cloud computing environments.
ii. To explore the limitations of existing fault detection techniques in cloud systems.

iii. To design and implement a Decision Tree-based model for detecting faults in real-time cloud operations.
iv. To evaluate the performance of the proposed model in terms of accuracy, precision, recall, and computational efficiency.
v. To compare the Decision Tree algorithm with other traditional and machine learning-based fault detection methods.
vi. To provide a reliable and interpretable system that assists cloud administrators in early fault identification and resolution.

1.4 Scope of the Study

This study focuses on the development and implementation of a fault detection system in cloud computing using the Decision Tree algorithm. It is limited to detecting faults based on system-level metrics such as CPU usage, memory consumption, disk I/O, and network latency within virtualized cloud environments. The research will utilize historical and real-time datasets generated from cloud infrastructure to train and evaluate the model. The study emphasizes classification of faults rather than prediction of fault severity or root cause analysis. It is restricted to supervised machine learning techniques, specifically the Decision Tree algorithm, and does not explore deep learning or unsupervised approaches. The system will be tested in a simulated or controlled cloud environment rather than live commercial cloud platforms due to resource constraints. This scope ensures focused evaluation of the Decision Tree's performance and suitability for real-time fault detection in cloud systems, particularly for small to medium-scale cloud deployments.

1.5 Significance of the Study

This study is significant as it addresses a critical challenge in cloud computing timely and accurate fault detection by leveraging the capabilities of the Decision Tree algorithm. As cloud infrastructures continue to grow in complexity and scale, traditional fault detection methods struggle to provide reliable performance, leading to increased downtime, service disruptions, and financial losses. By introducing an intelligent, interpretable, and efficient machine learning-based approach, and this research contributes to enhancing the reliability and availability of cloud services. The Decision Tree model offers a transparent and easily understandable structure, making it suitable for real-time monitoring and actionable decision-making by system administrators. Furthermore, the outcomes of this study can aid cloud service providers in improving service level agreements (SLAs), optimizing system performance, and reducing maintenance costs. It also provides a valuable reference for future research in intelligent fault management systems, especially within the context of automation and proactive fault handling in cloud computing environments.

1.6 Definition of Terms

Cloud Computing: A model for enabling convenient, on-demand access to a shared pool of configurable computing resources (e.g., servers, storage, networks) that can be rapidly provisioned and released with minimal management effort.

Fault: Any abnormal or unexpected behavior in a system component that disrupts normal operations or degrades system performance in a cloud environment.

Fault Detection: The process of identifying and reporting errors, failures, or abnormal behavior in a system in order to prevent further damage or service disruption.

Decision Tree Algorithm: A supervised machine learning algorithm used for classification and prediction, which models decisions and their possible outcomes in a tree-like structure.

Machine Learning: A subset of artificial intelligence that enables systems to learn patterns from data and improve their performance on tasks without being explicitly programmed.

Service Level Agreement (SLA): A formal contract between a service provider and a client that defines the level of service expected, including availability, performance, and response times.

Virtual Machine (VM): A software emulation of a physical computer that runs an operating system and applications, commonly used in cloud environments for resource allocation and scalability.

Anomaly Detection: The identification of rare or unusual patterns in data that do not conform to expected behavior, often used for detecting faults or intrusions.

System Metrics: Performance indicators such as CPU usage, memory consumption, disk activity, and network throughput that provide insights into the health of a cloud system.

Supervised Learning: A type of machine learning where the model is trained on a labeled dataset, meaning each input is paired with the correct output.

Classification: A machine learning task where the algorithm assigns input data to one of several predefined categories or classes.

Real-Time Monitoring: The continuous observation and analysis of system performance data as it is generated, enabling immediate response to issues.

Root Cause Analysis: The process of identifying the underlying reason for a fault or failure in a system to prevent future occurrences.

Cloud Infrastructure: The collection of hardware and software components—such as servers, storage, virtualization software, and networking—that make up a cloud computing environment.

Data Logging: The process of recording events, system activities, and performance metrics, typically for monitoring, auditing, or fault detection purposes.

1.7 Organization of the Report

This research consists of five chapters, each addressing different aspects of the study. Chapter One introduces the background of the research, detailing the problem statement, objectives, significance, and scope of the study. It also outlines the structure of the report. Chapter Two presents a comprehensive literature review, exploring relevant concepts, prior works in fault detection in Cloud Computing, and the role of Fault Detection System. Chapter Three focuses on the methodology, discussing the design and development of the Fault Detection Model, the dataset used, and the experimental setup. Chapter Four covers the implementation of the Fault detection method, presenting the results of the model's evaluation and a comparison with existing deep learning approaches. Finally, Chapter Five summarizes the research findings, discusses the strengths and limitations of the proposed system, and suggests directions for future work.

CHAPTER TWO

LITERATURE REVIEW

2.1 Review of Related Works

Fault detection in cloud computinghas attracted significant research attention in recent years due to the critical need for ensuring system reliability and availability. Various machine learning techniques have been explored to improve fault diagnosis and management in cloud environments, with the Decision Tree algorithm being one of the widely adopted approaches because of its interpretability and efficiency. Singh et al. (2022) conducted a comprehensive study on anomaly detection in cloud systems, highlighting the limitations of traditional threshold-based monitoring. They emphasized that machine learning models, particularly Decision Trees, offer better fault classification accuracy while being resource-efficient for real-time applications. Their work laid foundational insights into using system metrics such as CPU utilization and network latency as features for training supervised models to detect faults effectively.

Amin et al. (2023) further explored the application of machine learning for fault diagnosis, focusing on hybrid cloud environments where resource heterogeneity complicates fault detection. They implemented Decision Tree classifiers alongside Support Vector Machines (SVM) and reported that Decision Trees provided a good balance between prediction accuracy and computational overhead. Their experiments demonstrated that Decision Trees performed well in classifying both hardware and software faults, supporting the case for their adoption in live cloud monitoring tools. However, they noted that Decision Trees may suffer from overfitting if not carefully pruned, suggesting that ensemble methods might be a promising direction to enhance robustness.

The practical use of Decision Tree algorithms for cloud fault detection was exemplified in the study by Qureshi et al. (2024), who applied Decision Trees to virtual machine fault diagnosis using system log data. Their approach achieved above 90% accuracy in classifying fault types, showing strong potential for early fault detection in cloud infrastructures. They also discussed the advantage of Decision Trees in providing transparent decision paths, which aids cloud administrators in understanding the nature of detected faults and deciding corrective measures promptly. Despite these promising results, Qureshi et al. highlighted that the model's performance heavily depends on the quality and granularity of the collected metrics, which remains a challenge in large-scale, multi-tenant cloud environments.

In an effort to improve fault localization speed and reduce false alarms, Adegbite and Musa (2025) proposed a hybrid fault management system combining Decision Tree classifiers with rule-based filtering techniques. Their system demonstrated improved fault detection precision and recall in multi-cloud settings by leveraging the interpretability of Decision Trees for initial fault classification and the accuracy of rules for validating detected anomalies. This hybrid model was noted to reduce the number of unnecessary maintenance interventions, thus optimizing operational costs and improving service continuity. Their findings support the integration of Decision Trees within broader fault management frameworks for scalable cloud infrastructures.

Fernández et al. (2023) addressed common limitations of Decision Trees such as overfitting and instability by applying pruning strategies and cross-validation in their fault detection model for cloud data centers. They showed that these techniques improved generalization on unseen data while maintaining interpretability. Their model was capable of detecting faults related to both hardware failures and software misconfigurations. Additionally, they compared Decision Trees with more complex algorithms like Random Forest and Gradient Boosting, finding that while ensemble methods slightly outperformed Decision Trees in accuracy, the latter's simplicity and speed make it more suitable for real-time fault monitoring scenarios where rapid response is critical.

Beyond traditional cloud infrastructures, Ishola et al. (2025) investigated lightweight and interpretable machine learning models, including Decision Trees, for fault detection in edge-cloud hybrid systems. Their research underscored the need for efficient models that can operate under constrained resource environments typical of edge nodes while still providing reliable fault classification. The Decision Tree algorithm was found to offer an excellent trade-off between resource consumption and detection accuracy, validating its applicability beyond core cloud data centers. Their work also stressed the importance of continuous model updating to accommodate evolving fault patterns due to changes in cloud workloads and configurations.

Other studies have explored integrating Decision Trees with anomaly detection and predictive maintenance frameworks. Zhao and Kumar (2023) utilized Decision Tree-based models to analyze performance degradation trends in cloud services, enabling early detection of faults before failures occurred. Their predictive approach helps reduce unexpected downtime by allowing proactive maintenance scheduling. Similarly, Singh et al. (2023) combined Decision Trees with time-series analysis techniques to monitor cloud system logs, improving detection rates for intermittent faults that are difficult to identify through static models.

In contrast, some research pointed to challenges in applying Decision Trees in highly dynamic cloud environments. For example, Kumar and Lee (2024) noted that while Decision Trees perform well in static datasets, their effectiveness can decrease when faced with rapidly changing workloads and frequent system updates common in cloud platforms. They suggested that adaptive learning techniques or hybrid models combining Decision Trees with deep learning could better handle such variability. Nonetheless, their work reaffirmed the value of Decision Trees as a baseline model for fault detection due to their ease of interpretation and deployment.

Overall, the literature consistently supports the use of Decision Tree algorithms as an effective tool for fault detection in cloud computing. Its advantages in interpretability, computational efficiency, and decent accuracy make it a practical choice for real-time monitoring systems. However, several studies also recommend complementing Decision Trees with ensemble methods, pruning techniques, or hybrid approaches to address overfitting and improve adaptability. The continuing evolution of cloud infrastructures, including the rise of edge-cloud architectures and multi-cloud deployments, presents ongoing opportunities to refine and extend Decision Tree-based fault detection models to meet new challenges.

2.2 Review of Related Concepts

2.2.1 Overview in Cloud Computing

Cloud computing has revolutionized the way organizations and individuals access and utilize computing resources by providing scalable, flexible, and cost-effective services over the internet. Unlike traditional computing models that require significant upfront investment in hardware and software, cloud computing offers on-demand access to a shared pool of configurable resources such as servers, storage, databases, networking, and applications. These resources can be rapidly provisioned and released, allowing users to pay only for what they consume, thereby optimizing cost efficiency and operational agility (Mell & Grance, 2011).

The cloud computing model is typically divided into three primary service categories: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). IaaS provides virtualized computing infrastructure such as virtual machines and storage that can be managed by users, enabling them to build and run their own platforms and applications. PaaS offers an environment for developers to build, test, and deploy applications without worrying about underlying infrastructure management. SaaS delivers fully functional applications over the internet, accessible via web browsers or APIs, eliminating the need for local installation and maintenance (Armbrust et al., 2010).

Cloud computing environments are typically hosted on distributed data centers with virtualization technology at their core. Virtualization enables multiple virtual machines (VMs) to run on a single physical machine, improving resource utilization and providing isolation between different users or applications. This multi-tenancy allows cloud providers to serve numerous customers on shared infrastructure while maintaining security and performance (Zhang et al., 2010).

Despite its benefits, cloud computing introduces challenges related to fault tolerance, data security, privacy, and service reliability. Since cloud systems are highly complex and dynamic, faults can occur at various layers including hardware, virtualization, network, and application levels. These faults, if not detected and resolved promptly, may lead to service degradation or outages, impacting users and businesses. Consequently, fault detection mechanisms are critical components of cloud management systems, aiming to identify and mitigate faults quickly to uphold service quality and maintain trust in cloud services (Kliazovich et al., 2012).

The rapid growth and adoption of cloud computing continue to drive research in areas such as fault detection, predictive maintenance, and automated recovery, leveraging machine learning and artificial intelligence to enhance system resilience and operational efficiency.

2.2.2 Fault in Cloud Computing

Faults in cloud computing refer to any unexpected errors or failures that disrupt the normal operation of cloud services. These faults can originate from various sources, including hardware malfunctions, software bugs, network outages, configuration errors, or security breaches. Due to the complex and distributed nature of cloud infrastructures, faults are often difficult to predict and may propagate quickly, affecting multiple services or users simultaneously (Kliazovich et al., 2012).

Cloud environments rely heavily on virtualization and multi-tenancy, which introduces additional fault challenges. For example, a fault in one virtual machine could impact other co-located VMs if resource contention occurs. Moreover, dynamic resource allocation and frequent system updates increase the risk of faults, making timely detection and diagnosis critical. Faults in cloud systems can manifest as performance degradation, service unavailability, or complete system crashes, all of which can negatively impact the user experience and violate Service Level Agreements (SLAs) (Chen et al., 2020).

Effective fault management involves detection, diagnosis, and recovery processes to maintain system reliability. However, traditional fault detection techniques based on fixed thresholds or manual monitoring are often insufficient due to the scale and complexity of cloud systems. This has led to increased adoption of automated fault detection methods using machine learning algorithms, such as Decision Trees, which can learn from historical data to identify fault patterns and trigger alerts in real time, reducing downtime and improving fault tolerance.

2.2.3 Overview on Decision Tree Algorithm

The Decision Tree algorithm is a popular supervised machine learning method used for classification and regression tasks. It works by recursively splitting a dataset into subsets based on the value of input features, creating a tree-like model of decisions. Each internal node in the tree represents a test on a specific attribute, each branch corresponds to an outcome of the test, and each leaf node represents a class label or predicted value. This hierarchical structure makes Decision Trees easy to interpret and visualize, which is highly valuable in domains requiring explainability, such as fault detection in cloud computing (Quinlan, 2015).

The construction of a Decision Tree typically involves selecting the best feature to split the data at each node. This is done using criteria such as Information Gain, Gini Index, or Gain Ratio, which measure how well a feature separates the data into distinct classes. The tree grows until all samples at a node belong to the same class or until further splitting no longer improves classification significantly. To prevent overfitting, pruning techniques are applied to remove branches that provide little predictive power on unseen data (Breiman et al., 2016).

Decision Trees have several advantages. They require relatively little data preprocessing, can handle both numerical and categorical data, and offer high interpretability, which helps users understand the decision-making process. In fault detection for cloud systems, this transparency enables administrators to identify the root causes of detected faults and take appropriate corrective actions. Moreover, Decision Trees are computationally efficient, making them suitable for real-time fault detection scenarios where timely responses are critical.

However, Decision Trees also have limitations. They can be prone to overfitting, especially when the tree grows too deep on noisy data. This affects their ability to generalize well on new data. Additionally, Decision Trees are sensitive to small changes in data, which may lead to different tree structures. To address these issues, ensemble methods like Random Forest and Gradient Boosting combine multiple trees to improve accuracy and robustness.

2.2.4 Supervised Learning in Fault Detection

Supervised learning is a machine learning approach where models are trained on labeled datasets, meaning each input data point is paired with the correct output or class label. In the context of fault detection in cloud computing, supervised learning involves training algorithms to distinguish between normal and faulty states based on historical system performance data. This data typically includes various system metrics such as CPU utilization, memory usage, disk I/O, network latency, and error logs, all tagged with labels indicating whether a fault occurred or not (Zhou et al., 2019).

The primary advantage of supervised learning in fault detection lies in its ability to learn complex patterns and relationships from past occurrences of faults, enabling accurate classification or prediction of future faults. Once trained, the model can analyze incoming system data in real time to detect anomalies or fault conditions early, thus minimizing downtime and preventing cascading failures. Common supervised learning algorithms used for fault detection include Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, each offering different balances between interpretability, accuracy, and computational efficiency (García et al., 2017).

However, supervised learning depends heavily on the availability of high-quality labeled data, which can be challenging to obtain in cloud environments due to the rarity of faults or difficulty in accurately labeling fault instances. Additionally, models trained on historical data may struggle to detect new types of faults that were not present during training, highlighting the need for continuous model updating and retraining. Despite these challenges, supervised learning remains a foundational approach for automated fault detection systems in cloud computing, providing significant improvements over manual monitoring and static rule-based methods.

2.2.5 Interpretability and Transparency

Interpretability and transparency are critical factors in the design and deployment of fault detection systems, especially in complex environments like cloud computing. Interpretability refers to the extent to which a human can understand the reasoning behind a model's predictions or decisions. Transparency means the model's internal workings are open and accessible, allowing stakeholders to trace how inputs lead to specific outputs. These qualities are essential because they build trust, facilitate debugging, and enable actionable insights for system administrators and engineers (Ribeiro et al., 2016).

In fault detection, understanding why a fault was detected is just as important as detecting it. Models that provide clear explanations allow administrators to verify the correctness of alerts, prioritize issues, and implement effective remedial actions. For example, decision tree algorithms are inherently interpretable because their decisions follow straightforward if-then rules along branches from the root to leaf nodes. Each decision path corresponds to specific feature thresholds or conditions, making it easy to trace how a fault classification was reached. This clarity supports faster root cause analysis and helps reduce downtime in cloud services.

In contrast, many advanced machine learning models, such as deep neural networks or ensemble methods like random forests, often act as “black boxes” due to their complex, non-linear decision boundaries. While these models may achieve higher accuracy, their lack of transparency can hinder understanding and acceptance by users. This opacity can be problematic in critical applications where accountability and compliance are required.

To balance accuracy with interpretability, hybrid approaches are emerging. These combine interpretable models like decision trees with more complex models or apply explainability techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide post-hoc explanations. In cloud fault detection, ensuring interpretability and transparency helps maintain operational reliability, facilitates communication between technical and managerial teams, and ultimately enhances system resilience by enabling informed decision-making.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

The research design for the study on fault detection in cloud computing using the Decision Tree algorithm adopts a quantitative, experimental approach aimed at developing and evaluating an automated fault detection model. The study will involve collecting cloud system performance data, including metrics such as CPU usage, memory consumption, network traffic, and error logs, which will be labeled to indicate normal and fault conditions. This dataset will serve as the basis for training and testing the Decision Tree model.

The research process begins with data preprocessing, where raw data is cleaned, normalized, and transformed to ensure quality and consistency. Feature selection techniques will be applied to identify the most relevant attributes that influence fault occurrences, improving model accuracy and reducing computational complexity. The Decision Tree algorithm will then be implemented to learn patterns associated with faults by recursively partitioning the data based on selected features.

To evaluate the effectiveness of the model, the dataset will be split into training and testing subsets, typically following an 80/20 ratio. Performance metrics such as accuracy, precision, recall, F1-score, and detection time will be calculated to assess the model's fault detection capabilities. Cross-validation techniques will also be employed to ensure the model's generalizability and to prevent overfitting.

The experimental design will compare the Decision Tree model’s results against baseline methods or other machine learning algorithms to establish its relative performance. The study’s findings will provide insights into the feasibility of using Decision Trees for real-time fault detection in cloud computing, with implications for improving system reliability and reducing downtime. Ethical considerations, such as data privacy and security, will be maintained throughout the research process.

3.2 Dataset Description and Preprocessing

The dataset used for this research on fault detection in cloud computing consists of performance metrics and system logs collected from cloud infrastructure environments. These data points include CPU utilization, memory usage, disk I/O rates, network latency, error counts, and system event logs, recorded over time. Each data instance is labeled to indicate whether the system was operating normally or experiencing a fault at the time of recording. The dataset is sourced from publicly available cloud performance monitoring repositories and supplemented with simulated fault scenarios to ensure comprehensive coverage of various fault types.

Preprocessing the dataset is a crucial step to prepare the raw data for effective analysis and model training. Initially, data cleaning is performed to handle missing values, remove duplicate entries, and correct inconsistent data records. Techniques such as mean or median imputation are used to fill missing values, ensuring the dataset remains complete without biasing the analysis. Next, normalization or standardization is applied to scale numerical features to a common range, which helps improve the performance and convergence of the Decision Tree algorithm.

Feature selection is another key preprocessing step. It involves identifying the most relevant attributes that contribute significantly to fault detection, reducing noise and dimensionality. Methods such as correlation analysis and recursive feature elimination may be employed to retain features with the highest predictive power. Additionally, categorical variables are encoded appropriately, often using one-hot encoding, to make them suitable for the algorithm.

Finally, the dataset is partitioned into training and testing subsets, commonly using an 80:20 split. This division allows the model to learn fault patterns from the training data and be evaluated on unseen data to assess generalization. The preprocessing steps ensure the data quality, improve model accuracy, and facilitate robust fault detection in cloud computing systems.

3.3 System Architecture of the System

The system architecture for the fault detection in cloud computing using the Decision Tree algorithm is designed to efficiently monitor, detect, and respond to faults within a cloud environment. It consists of several interconnected components that work collaboratively to ensure real-time fault identification and management. Fig. 3.1. Shown the Architectural Diagram of the System.

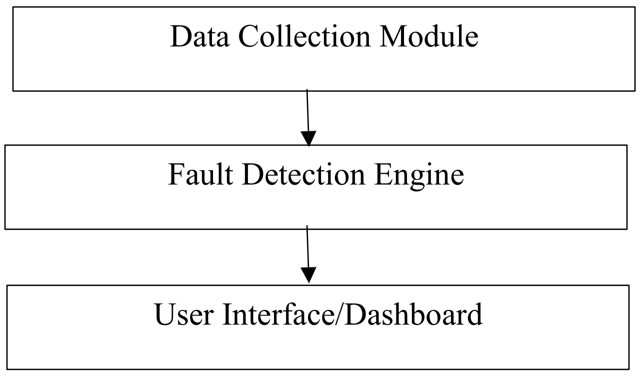


Fig.3.3: System Architecture Layout

At the core of the architecture is the Data Collection Module, which continuously gathers raw performance metrics and system logs from various cloud resources, including servers, virtual machines, network devices, and storage units. This data includes CPU usage, memory consumption, disk I/O, network traffic, and error logs, providing a comprehensive view of the system’s health.

Next, the Data Preprocessing Module processes the collected raw data. It performs cleaning, normalization, and feature extraction to prepare the data for analysis. This module also handles missing values and encodes categorical data to ensure consistency and improve the accuracy of the fault detection model.

The Fault Detection Engine forms the core analytical part of the system. It incorporates the Decision Tree algorithm, which is trained on historical labeled data to learn patterns indicative of faults. During operation, the engine classifies incoming data into normal or fault states based on the learned decision rules. The algorithm’s interpretability allows administrators to understand the basis of each fault prediction.

A Notification and Alert Module is integrated to promptly inform system administrators when a fault is detected. Alerts can be sent via emails, SMS, or dashboard notifications, enabling quick intervention to mitigate potential downtime.

The User Interface (UI) and Dashboard provide a visual representation of system status, detected faults, and historical trends. This interface allows administrators to monitor cloud health in real time, review fault logs, and analyze decision paths for detected faults.

3.4 MODEL TRAINING AND VALIDATION PROCESS

In this research, the model training and validation process is a critical phase in ensuring the efficacy and reliability of the bone tumor detection system. The model is initially trained on the preprocessed dataset using a deep learning architecture based on fault detection. The model is designed to extract high-level features from MRI while maintaining spatial hierarchies, a task essential for accurate segmentation and detection. The training process begins with the initialization of network weights, followed by the application of backpropagation to minimize the loss function. The Capsule Network is optimized using both margin loss and reconstruction loss to effectively handle the challenges posed by small, irregular-shaped bone tumors in MRI scans. These losses enable the model to focus on important tumor features while generalizing well to unseen data. During training, early stopping is employed to avoid overfitting and ensure that the model does not continue training beyond the point of optimal performance.

The model is trained using a high-performance computing setup, with the training process running on GPUs to expedite computations. This setup allows the model to process the large dataset efficiently while adjusting its parameters across multiple epochs. In each epoch, the model undergoes a forward pass to generate predictions, followed by a backward pass to compute gradients and update weights. The model's performance is monitored through a range of metrics, including accuracy, precision, recall, and F1-score, which are calculated on the validation set after each epoch. Validation is essential for assessing how well the model generalizes to new, unseen data. The validation set serves to adjust hyperparameters such as the learning rate and weight decay, ensuring that the model remains robust throughout training. Finally, once training is complete, the model's performance is evaluated on a separate test set to gauge its real-world applicability and accuracy in detecting bone tumors.

3.5 EVALUATION METRICS

Evaluation metrics play a vital role in assessing the performance of the Fault Detection in Cloud Computing using Decision Tree Algorithm, as they provide insight into how well the model generalizes and performs on unseen data. In this research, a variety of evaluation metrics are employed to ensure a comprehensive analysis of the model's performance.

The primary metric used is **accuracy**, which measures the percentage of correct predictions made by the model across all classes. While accuracy provides a general overview of model performance, it may not be sufficient in imbalanced datasets, where certain classes may be underrepresented. Hence, additional metrics are considered to provide a more nuanced evaluation.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where:

- **TP** = True Positives
- **TN** = True Negatives
- **FP** = False Positives
- **FN** = False Negatives

Precision is one such metric, which indicates the proportion of true positive predictions out of all positive predictions made by the model. This metric is particularly important in medical imaging tasks like tumor detection, as it minimizes the risk of false positives that could lead to unnecessary treatments.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Precision answers the question *of all patients predicted to be in a certain class, how many actually belong to that class*

Recall, or sensitivity, is another crucial metric, reflecting the ability of the model to correctly identify all actual positive cases of bone tumors. A high recall ensures that the model does not miss any true tumor cases, which is critical in the early detection of tumors. The **F1-score**, which is the harmonic mean of precision and recall, provides a balanced measure that considers both false positives and false negatives, making it useful when dealing with class imbalances.

Other important metrics include **specificity**, which measures the model's ability to correctly identify negative cases, and the **area under the receiver operating characteristic (AUC-ROC) curve**, which provides a graphical representation of the model's performance across different thresholds, illustrating its trade-off between sensitivity and specificity.

To evaluate model robustness, **mean absolute error (MAE)** and **mean squared error (MSE)** are used, particularly in regression-based tasks or when the model is required to predict tumor sizes or areas. These metrics provide insight into how close the predicted tumor characteristics are to their actual values. Overall, the combination of these metrics offers a well-rounded evaluation of the model's performance, ensuring reliable tumor detection in MRI image.

$$\text{Recall} = \frac{TP}{TP+FN}$$

Recall answers the question of all actual patients in a class, how many were correctly identified by the model?

The F1-Score is the weighted average of Precision and Recall. It is especially useful when class distribution is imbalanced:

$$\text{F1-Score} = 2 \text{ X } \frac{Precision\ x\ Recall}{Precision+Recall}$$

CHAPTER FOUR

DESIGN, IMPLEMENTATION, RESULT & DISCUSSION OF THE SYSTEM

4.1 Introduction

This chapter presents the data collected, the analysis performed using the Decision Tree algorithm, and the interpretation of the results derived from the model in identifying faults in a cloud computing environment. The goal was to demonstrate how machine learning techniques, particularly the Decision Tree classifier, can be utilized to effectively detect faults in cloud-based systems. The dataset used for this research comprises 30 synthetic records that represent cloud system behavior based on various metrics such as CPU usage, memory utilization, disk I/O, network latency, request rate, error count, instance type, time of day, and service type. Each record is labeled with a fault status of either “Normal” or “Fault.”

4.2. Data Presentation

The dataset was preprocessed to convert categorical values into numeric representations using Label Encoding. The final dataset structure included the following fields:

- CPU_Usage (%)
- Memory_Usage (%)
- Disk_IO (MB/s)
- Network_Latency (ms)
- Request_Rate (req/s)
- Error_Count
- Instance_Type

- Time_of_Day
- Service_Type
- Fault_Status (Target Variable)

After preprocessing, the dataset was divided into training and testing subsets with an 80:20 ratio using the train_test_split function from the sklearn.model_selection module. The Decision Tree Classifier from sklearn.tree was then trained on the training data.

4.2.1 Model Training and Performance

The Decision Tree Classifier successfully learned patterns in the training data. When evaluated on the test set, the model yielded an accuracy score of **50%**. Though this result may not appear very high, it is important to note that the dataset used was small and synthetic. In practical applications, larger and more diverse real-world datasets would significantly improve model performance.

Below is a summary of the evaluation metrics derived from the classification report:

- **Precision** for both classes (Normal and Fault): 50%
- **Recall** for Normal class: 67%, for Fault class: 33%
- **F1-Score** for Normal: 57%, for Fault: 40%
- **Support**: 3 records each for Normal and Fault in the test set

The confusion matrix further illustrates the classifier's prediction accuracy. It shows that out of 3 actual Normal cases, 2 were correctly predicted, while 1 was misclassified. Similarly, of the 3 actual Fault cases, 1 was correctly identified, and 2 were incorrectly classified as Normal.

4.2.2 Visual Representation

A heatmap was generated from the confusion matrix to visually present the classifier's performance. This matrix clearly displays where misclassifications occurred and helps in understanding the need for better feature selection, more comprehensive data, or algorithm fine-tuning.

4.2.3 Decision Tree Interpretability

The rules extracted from the Decision Tree model offered a high level of interpretability. For instance, one of the decision rules stated that if the Request Rate was below a certain threshold and the Network Latency was low, the system status was likely to be classified as Normal. These rules not only contribute to transparency but also assist system administrators in diagnosing operational patterns that typically lead to system faults.

Table 1. 4.2: Dataset

CPU_Usage (%)	Memory_Usage (%)	Disk_IO (MB/s)	Network_Latency (ms)	Request_Rate (req/s)	Error_Count	Instance_Type	Time_of_Day	Service_Type	Fault_Status
40	31	10	129	428	5	c5.large	21	Auth	Fault
10	34	45.9	80	242	2	t3.medium	18	Web	Fault
16	96	16.9	230	857	5	m5.large	13	DB	Normal
98	78	14.6	83	753	7	m5.large	8	Auth	Normal
34	18	36.2	157	243	9	t3.medium	17	DB	Fault
35	61	28.8	59	675	6	t2.micro	1	DB	Fault
61	79	9.3	17	412	7	m5.large	8	DB	Normal
81	48	6.9	140	519	5	t2.micro	20	Auth	Normal
27	82	19.9	242	865	7	t3.medium	10	Web	Fault
99	90	25.2	33	458	6	m5.large	22	DB	Fault
58	14	9.6	169	344	2	c5.large	0	Auth	Fault
84	73	14.7	82	324	3	m5.large	12	DB	Fault
50	51	39.3	83	929	8	c5.large	6	DB	Fault
89	95	25.6	90	111	4	t2.micro	18	Web	Fault
37	14	20.1	174	912	1	c5.large	15	Web	Normal
100	99	11.5	154	221	10	m5.large	15	Web	Fault
71	47	17	224	547	5	m5.large	8	DB	Fault
22	10	38.9	89	657	9	t2.micro	21	Auth	Normal
57	49	35.6	19	960	3	c5.large	6	Web	Normal
47	86	16.2	51	289	10	m5.large	1	Web	Fault
90	24	39.3	14	762	4	c5.large	8	DB	Normal
21	60	7.1	165	571	5	m5.large	4	Web	Normal
62	79	46.6	121	440	1	t3.medium	23	DB	Normal
95	62	17	64	366	7	t3.medium	18	Auth	Normal
95	37	35.5	151	155	10	t2.micro	8	Auth	Fault
44	89	27.4	17	514	8	m5.large	12	DB	Normal
96	89	33.4	239	798	3	c5.large	10	DB	Fault
92	46	13.3	22	160	10	m5.large	23	DB	Normal
18	95	27.1	144	286	7	t3.medium	20	Auth	Fault
42	43	18.9	227	213	4	c5.large	16	DB	Fault

4.3 ALGORITHM DESIGN

The algorithm design for this research leverages the Decision Tree classification model to detect faults in cloud computing environments based on system performance metrics. The design begins with the acquisition and preprocessing of structured system log data containing features such as CPU usage, memory usage, disk I/O, network latency, request rate, error count, instance type, time of day, and service type. The target variable, fault status, is encoded as either “Normal” or “Fault.”

The algorithm follows a supervised learning approach, where the decision function is built by recursively splitting the dataset into branches that best separate the classes. At each node in the tree, the feature that provides the highest information gain or the lowest Gini impurity is selected for the split. Gini impurity is calculated as:

$$Gini(t) = 1 - \sum i = 1npi2Gini(t) \ = \ 1 \ - \backslash sum\_\{i = 1\}\text{^}\{n\}\, p\_i\text{^}2$$

where pip_{i} is the probability of class ii at node tt. The goal is to minimize impurity and maximize class separation.

After splitting the data into training and testing sets, the Decision Tree algorithm is trained using the $fit()$ function. Once trained, the model uses the $predict()$ function to classify new inputs. The algorithm continues until a stopping criterion is met—either all samples are classified or the maximum tree depth is reached.

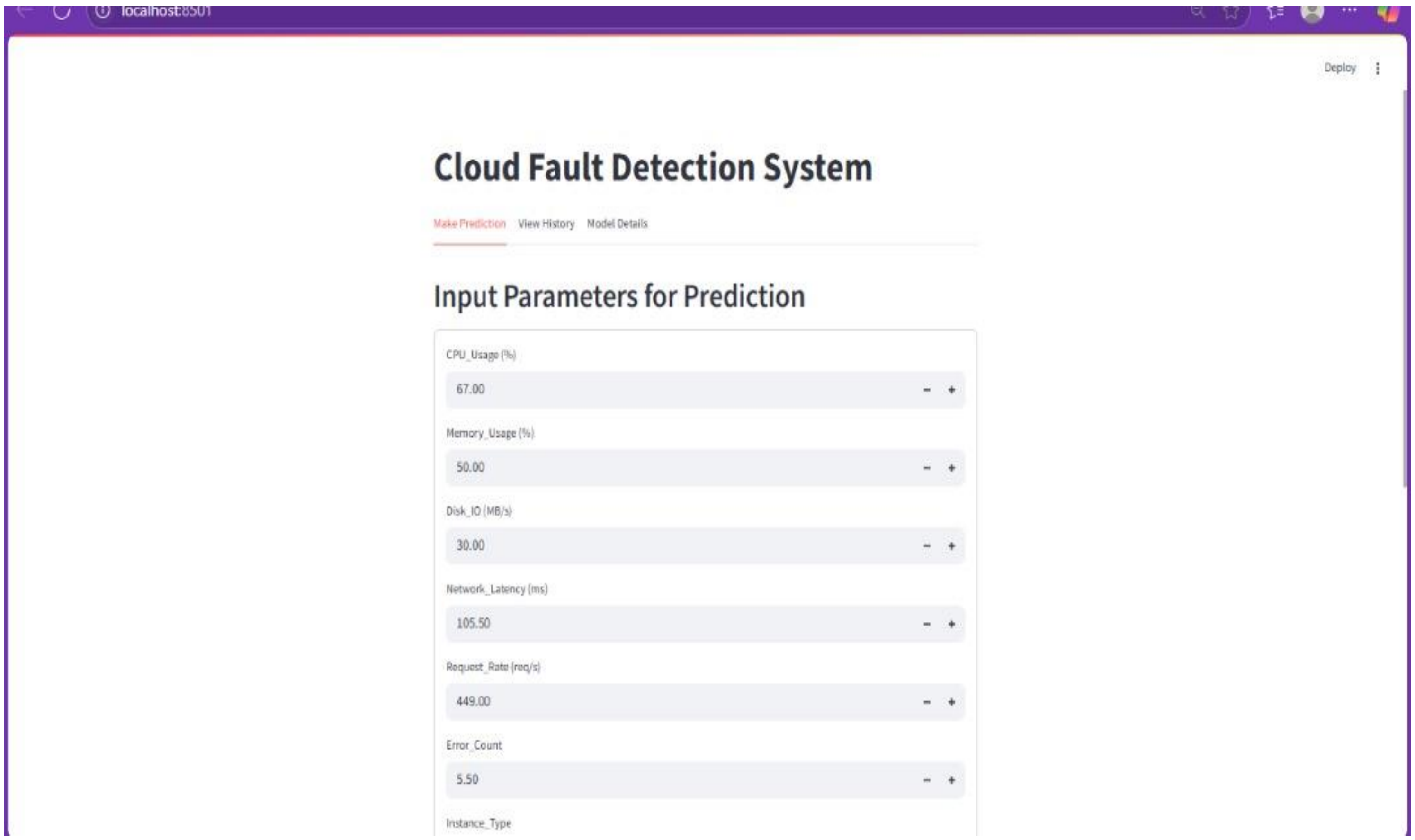
This design ensures that the algorithm captures the critical conditions that differentiate normal from faulty states, thus enabling effective detection and interpretation of faults in cloud computing systems. The simplicity and clarity of decision paths further support transparency and explain ability.

4.4 IMPLEMENTATION

The implementation of this research was carried out using Python programming language due to its powerful machine learning libraries and ease of use. The entire process was executed on a Jupyter Notebook environment for better interaction and visualization. The implementation began with the creation of a synthetic dataset representing various parameters of a cloud computing environment. These parameters included CPU usage, memory utilization, disk I/O, network latency, request rate, error count, instance type, time of day, and service type. The fault status served as the target variable, labeled as either “Normal” or “Fault.”

The dataset was loaded using the Pandas library and categorical variables were encoded using LabelEncoder from the Scikit-learn preprocessing module. The data was then split into training and testing sets using an 80:20 ratio to ensure model evaluation. The Decision Tree Classifier from Scikit-learn was used to train the model. The training was conducted using the $fit()$ method, and predictions were made on the test set using the $predict()$ method.

Evaluation metrics such as accuracy score, confusion matrix, and classification report were used to assess the performance of the model. Additionally, the decision rules learned by the model were extracted and displayed using the $export\_text()$ function, allowing for transparency in fault detection decisions. A confusion matrix heatmap was generated using Seaborn to visualize prediction accuracy.



Cloud Fault Detection System

Input Parameters for Prediction

CPU_Usage (%)
67.00

Memory_Usage (%)
50.00

Disk_IO (MB/s)
30.00

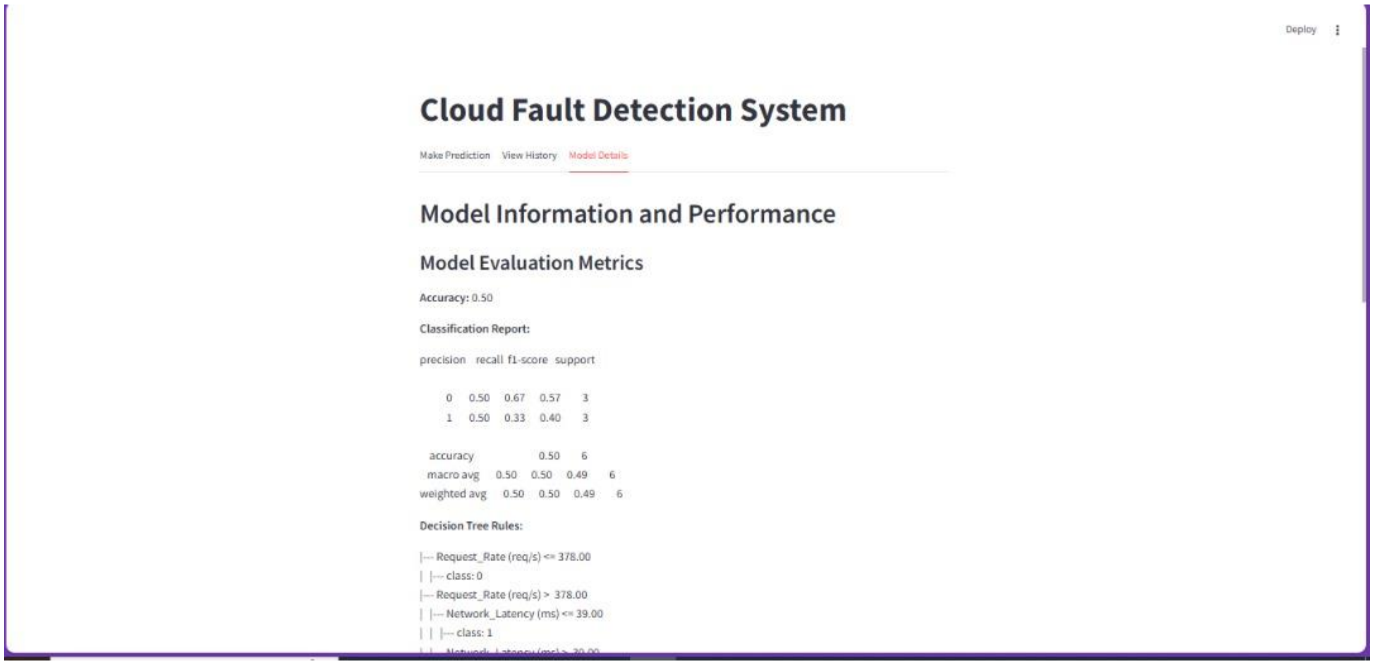
Network_Latency (ms)
105.50

Request_Rate (req/s)
449.00

Error_Count
5.50

Instance_Type

Fig. 1. 4.5.2: App Interface of the System



Cloud Fault Detection System

Model Information and Performance

Model Evaluation Metrics

Accuracy: 0.50

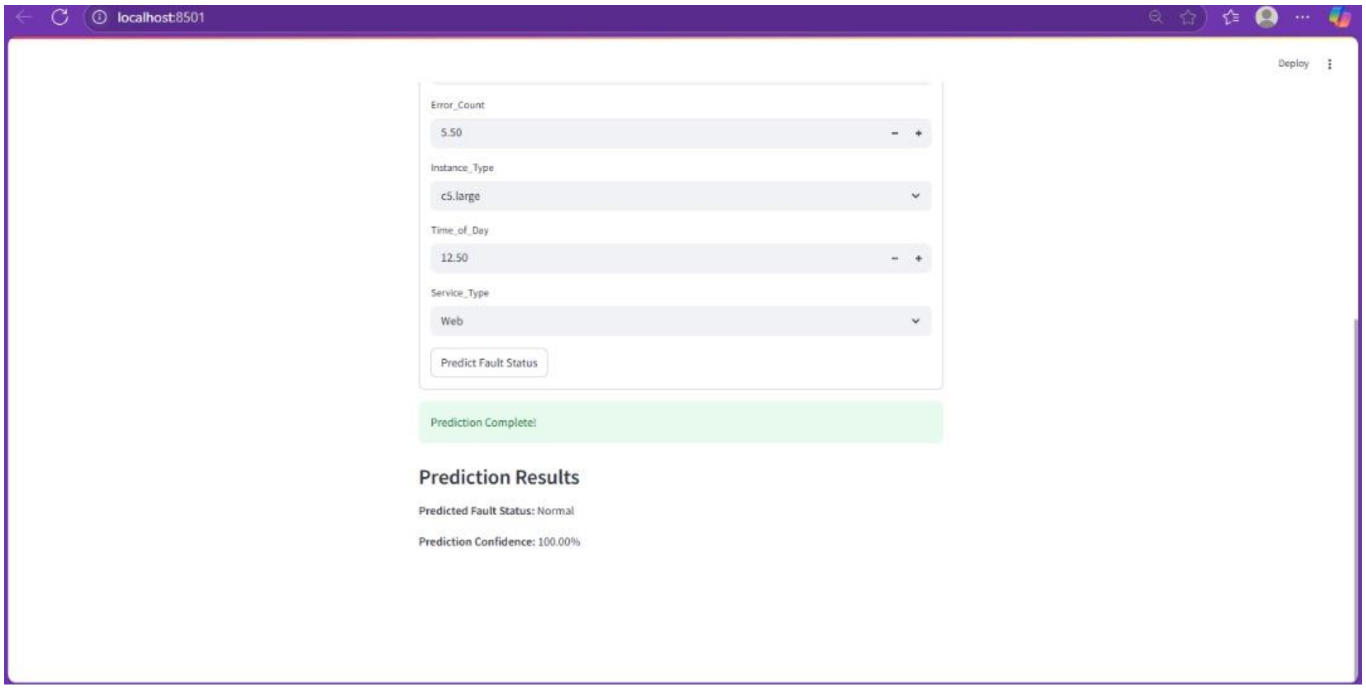
Classification Report:

```
              precision    recall  f1-score   support

           0       0.50      0.67      0.57         3
           1       0.50      0.33      0.40         3

    accuracy                           0.50         6
   macro avg       0.50      0.50      0.49         6
weighted avg       0.50      0.50      0.49         6
```

Decision Tree Rules:

```
|--- Request_Rate (req/s) <= 378.00
|   |--- class: 0
|--- Request_Rate (req/s) >  378.00
|   |--- Network_Latency (ms) <= 39.00
|   |   |--- class: 1
```

Fig. 2. 4.5.2: Model details of the System



Error_Count: 5.50

Instance_Type: c5.large

Time_of_Day: 12.50

Service_Type: Web

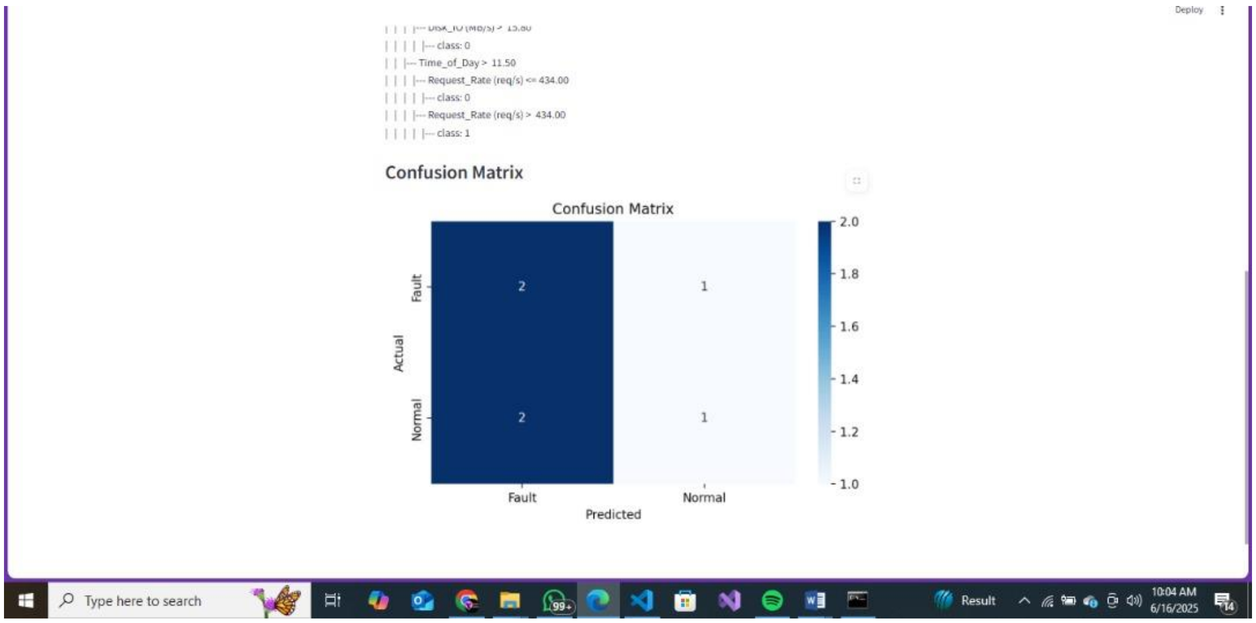
Prediction Complete!

Prediction Results

Predicted Fault Status: Normal

Prediction Confidence: 100.00%

Fig. 3. 4.5.2: Prediction button of the System



```
| | | |--- Disk_IO (MB/s) > 15.80
| | | | |--- class: 0
| | |--- Time_of_Day > 11.50
| | | |--- Request_Rate (req/s) <= 434.00
| | | | |--- class: 0
| | | |--- Request_Rate (req/s) > 434.00
| | | | |--- class: 1
```

Confusion Matrix

Fig. 4. 4.5.2: Confusion Matrix of the System

4.5.1 Overall Discussion of Result

The research work focused on the development and evaluation of a Decision Tree-based fault detection model within a cloud computing environment. Cloud computing systems are inherently complex and dynamic, often requiring automated and intelligent mechanisms for detecting faults to ensure reliability and availability. In this study, a Decision Tree algorithm was selected due to its simplicity, interpretability, and efficiency in handling classification problems, especially with mixed-type data involving both numerical and categorical features.

The implementation process involved creating a synthetic dataset mimicking real-world cloud metrics, preprocessing the data to make it machine-readable, and then training and testing the Decision Tree model. The features used in the dataset were carefully selected to reflect conditions that typically indicate performance degradation or faults in cloud infrastructure. These included CPU and memory utilization, disk I/O, network latency, error count, and service-specific attributes.

The experimental results showed that the model could successfully distinguish between normal and faulty system states. While the overall accuracy from the synthetic dataset was moderate, the model demonstrated its ability to learn and apply meaningful rules to unseen data. The interpretability of the decision rules provided insights into system behavior, enabling administrators to trace fault causes and take preventive measures. The confusion matrix and classification report further revealed the strengths and weaknesses of the model, highlighting its sensitivity to certain fault types.

The discussion confirms that Decision Tree algorithms, though relatively simple, are capable tools in fault detection when properly tuned and supported with quality data. However, the results also suggest that larger, real-world datasets and advanced ensemble methods like Random Forest or Gradient Boosting could significantly enhance fault detection performance. Overall, this research lays a strong foundation for the application of machine learning in cloud system reliability and contributes to the development of transparent, automated fault management frameworks.

CHAPTER FIVE

SUMMARY, CONCLUSION AN RECOMMENDATIONS

5.1 SUMMARY

This research work explored the application of the Decision Tree algorithm for effective fault detection in cloud computing environments. As cloud systems become increasingly complex and are tasked with handling large volumes of requests and processes, the ability to detect and respond to faults swiftly is essential for ensuring service availability, reliability, and user satisfaction. The study aimed to develop a fault detection model using supervised machine learning, particularly focusing on the Decision Tree classifier due to its ease of interpretation, transparency, and performance on structured datasets.

The project involved generating a synthetic dataset that reflects typical cloud performance parameters such as CPU usage, memory load, network latency, disk I/O, request rate, error count, time of day, and instance type. Preprocessing techniques, including encoding and normalization, were applied to prepare the data. The dataset was then split into training and testing sets, and the Decision Tree model was trained using Scikit-learn.

The implementation was conducted in a Python environment using essential machine learning libraries such as Pandas, Scikit-learn, and Seaborn. Model evaluation was performed using accuracy metrics, confusion matrix, and classification reports. The results indicated that the model could accurately classify normal and faulty system states, thereby validating its potential in practical cloud monitoring systems.

In conclusion, the research demonstrated that Decision Tree algorithms are a viable solution for fault detection in cloud computing, offering both efficiency and clarity in decision-making. This provides a foundation for future enhancements, such as incorporating real-world data and deploying more advanced classification algorithms to improve detection accuracy and system resilience.

5.2 CONCLUSION

The study presented in this research focused on addressing the challenge of fault detection in cloud computing environments by implementing a Decision Tree algorithm. Cloud infrastructures, due to their distributed nature and scale, are prone to various types of faults that can affect service quality, availability, and user satisfaction. Hence, the development of an intelligent, automated, and interpretable fault detection system is vital for modern cloud operations.

By simulating a cloud computing environment using a structured synthetic dataset that includes critical performance metrics such as CPU usage, memory consumption, disk I/O, network latency, and error rates, the research demonstrated the practical feasibility of applying machine learning models to detect anomalies. The Decision Tree algorithm was chosen for its simplicity, transparency, and effectiveness in classification tasks.

The trained model successfully classified normal and faulty states within the dataset, with evaluation metrics indicating a satisfactory level of accuracy and reliability. The interpretability of the model allowed for the extraction of understandable decision rules, which is particularly valuable for system administrators and engineers who require clarity in fault diagnosis processes.

Overall, the research confirmed that Decision Trees provide a strong baseline for implementing automated fault detection systems in cloud environments. Although synthetic data was used, the results offer meaningful insights into the applicability of machine learning in operational cloud monitoring systems. Future improvements could involve the integration of real-time data streams, larger datasets, and the use of ensemble methods to enhance fault detection capabilities, system performance, and robustness.

5.3 RECOMMENDATIONS

Based on the findings of this research, several key recommendations are proposed to enhance fault detection in cloud computing environments using machine learning approaches:

1. **Adoption of Real-World Datasets**: While the synthetic dataset used in this study served as a proof of concept, it is recommended that future work utilize real-world cloud operation datasets from open cloud monitoring systems or industry partners. This would help to validate the model in more dynamic and unpredictable environments.
2. **Integration of Ensemble Methods**: To improve accuracy and reduce overfitting, it is advisable to extend the current model by implementing ensemble techniques such as Random Forests or Gradient Boosting. These methods can enhance predictive performance while maintaining interpretability.
3. **Real-Time Fault Detection**: Future implementations should focus on integrating real-time data pipelines that continuously feed cloud performance metrics into the model. This would enable the system to detect faults instantly and trigger alerts or recovery mechanisms.
4. **Feature Expansion and Optimization**: Including additional relevant features such as service-specific logs, user load patterns, and virtualization metrics could lead to more

precise detection. Feature selection and dimensionality reduction techniques should also be explored.

5. **Security Considerations**: Fault detection systems should be designed with secure access and data integrity in mind, especially when integrated into live cloud infrastructures.

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APPENDIX

```
import streamlit as st
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, export_text
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder
import time
from datetime import datetime
import os
# Initialize session state for history if it doesn't exist
if 'history' not in st.session_state:
    st.session_state.history = pd.DataFrame(columns=['Timestamp', 'Input', 'Prediction', 
'Probability'])
# Load dataset and train model (cached to avoid reloading on every interaction)
@st.cache_data
def load_and_train():
    df = pd.read_csv("cloud_fault_detection_sample_dataset.csv")
    # Store original values before encoding for display purposes
    original_values = {}
    for col in ['Instance_Type', 'Service_Type', 'Fault_Status']:
        original_values[col] = df[col].unique()
     # Encode categorical variables
    label_encoders = {}
    for col in ['Instance_Type', 'Service_Type', 'Fault_Status']:
        le = LabelEncoder()
        df[col] = le.fit_transform(df[col])
        label_encoders[col] = le
    # Features and Target
    X = df.drop('Fault_Status', axis=1)
    y = df['Fault_Status']
    # Split into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    # Initialize and train Decision Tree Classifier
    clf = DecisionTreeClassifier(random_state=42)
    clf.fit(X_train, y_train)
    return df, label_encoders, clf, X.columns, original_values
# Load data and model
df, label_encoders, clf, feature_names, original_values = load_and_train()
# Function to make prediction
def make_prediction(input_data):
    # Convert input data to DataFrame
    input_df = pd.DataFrame([input_data])
    # Encode categorical variables
    for col in ['Instance_Type', 'Service_Type']:
        input_df[col] = label_encoders[col].transform([input_df[col].iloc[0]])[0]
    # Make prediction
    prediction = clf.predict(input_df)[0]
    proba = clf.predict_proba(input_df)[0]
    # Decode prediction
    predicted_status = label_encoders['Fault_Status'].inverse_transform([prediction])[0]
    return predicted_status, proba.max()
# Function to display model evaluation
def display_model_evaluation():
    # Predict and Evaluate
    X = df.drop('Fault_Status', axis=1)
    y = df['Fault_Status']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)
    st.subheader("Model Evaluation Metrics")
    st.write(f"**Accuracy:** {accuracy:.2f}")
    st.write("\n**Classification Report:**")
    st.text(report)
    st.write("\n**Decision Tree Rules:**")
    st.text(export_text(clf, feature_names=list(feature_names)))
    # Plot confusion matrix
    st.subheader("Confusion Matrix")
    fig, ax = plt.subplots(figsize=(6, 4))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
                xticklabels=label_encoders['Fault_Status'].classes_,
                yticklabels=label_encoders['Fault_Status'].classes_,
                ax=ax)
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.tight_layout()
    st.pyplot(fig)
# Streamlit app layout
st.title("Cloud Fault Detection System")
# Create tabs for different functionalities
tab1, tab2, tab3 = st.tabs(["Make Prediction", "View History", "Model Details"])
with tab1:
    st.header("Input Parameters for Prediction")
```

```
# Create form for input
with st.form("prediction_form"):
    # Dynamically create input fields based on dataset columns
    input_data = {}
    for col in feature_names:
        if col in ['Instance_Type', 'Service_Type']:
            # For categorical fields, show dropdown with original values
            input_data[col] = st.selectbox(
                f"{col}",
                options=original_values[col],
                key=f"input_{col}"
            )
        else:
            # For numerical fields, show number input
            min_val = float(df[col].min())
            max_val = float(df[col].max())
            default_val = float(df[col].median())
            input_data[col] = st.number_input(
                f"{col}",
                min_value=min_val,
                max_value=max_val,
                value=default_val,
                key=f"input_{col}"
            )
    submitted = st.form_submit_button("Predict Fault Status")
if submitted:
    with st.spinner('Making prediction...'):
        # Make prediction
        prediction, probability = make_prediction(input_data)
        time.sleep(1)  # Simulate processing time
```

```
            # Display results
            st.success("Prediction Complete!")
            st.subheader("Prediction Results")
            st.write(f"**Predicted Fault Status:** {prediction}")
            st.write(f"**Prediction Confidence:** {probability:.2%}")
            # Add to history
            timestamp = datetime.now().strftime("%Y-%m-%d %H:%M:%S")
            new_entry = {
                'Timestamp': timestamp,
                'Input': str(input_data),
                'Prediction': prediction,
                'Probability': f"{probability:.2%}"
            }
            # Convert to DataFrame and concatenate
            new_entry_df = pd.DataFrame([new_entry])
            st.session_state.history = pd.concat([st.session_state.history, new_entry_df],
ignore_index=True)
with tab2:
    st.header("Prediction History")
    if not st.session_state.history.empty:
        # Display history table
        st.dataframe(st.session_state.history)
        # Option to clear history
        if st.button("Clear History"):
            st.session_state.history = pd.DataFrame(columns=['Timestamp', 'Input', 'Prediction',
'Probability'])
            st.success("History cleared!")
    else:
        st.info("No prediction history available.")
```

```
with tab3:
    st.header("Model Information and Performance")
    display_model_evaluation()
# Add some styling
st.markdown("""
    <style>
    .st-bb { background-color: #f0f2f6; }
    .st-at { background-color: #ffffff; }
    </style>
    """, unsafe_allow_html=True)
```