National College of Ireland

ML-Powered Cloud Task Failure Prediction and Scalable Deployment on AWS

MSc Research Project

MSc in Cloud Computing

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MSc Project Submission Sheet

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Programme: ……MSc in Cloud Computing…… **Year:** …2024……..

Module: ……Research Project……..……..……

Supervisor: ……Aqeel Kazmi…..……..……

Submission Due Date: ……15-09-2025……..……

Project Title: ML-Powered Cloud Task Failure Prediction and Scalable Deployment on AWS

Word Count: ……7456…… **Page Count:** ……18……

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ML-Powered Cloud Task Failure Prediction and Scalable Deployment on AWS

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Abstract

Predicting task failures in large-scale cloud environments is critical for improving system reliability and managing Service Level Agreements. This project presents an end-to-end machine learning system for predicting cloud task failures using historical workload data from Google Borg traces. A Random Forest Classifier was trained to distinguish between failing and succeeding tasks based on features such as resource requests, memory usage, and CPU cycles. The resulting model was operationalized by building a Flask-based REST API that dynamically loads the model from Amazon S3. For deployment, the application was containerized using Docker and orchestrated on AWS using ECS Fargate, ensuring a serverless and scalable execution environment for the prediction service. The system's endpoint is exposed via an Application Load Balancer, with an attached Auto Scaling policy based on CPU utilization to handle variable prediction request loads, ensuring the API itself remains responsive. This work demonstrates a complete, production-ready pipeline for deploying a real-time, scalable, ML-powered classification service in a cloud-native fashion.

Keywords: Machine Learning, Failure Prediction, Cloud Computing, AWS, ECS Fargate, Docker, Random Forest, Auto Scaling, REST API, Google Borg Dataset.

1. Introduction

1.1. Background

In the modern era of cloud-based computing, efficient resource management has become a critical challenge, as organizations must balance application performance with cost under highly dynamic conditions **(Alharthi et al., 2024)**. This creates a persistent conflict: over-provisioning resources leads to unnecessary financial waste, while under-provisioning can degrade service quality and lead to costly violations of Service Level Agreements (SLAs). As modern cloud environments scale to run millions of tasks, manually allocating resources is not only impractical but also highly inefficient, creating a critical need for intelligent, automated systems.

The most common automated solution, threshold-based auto-scaling, is fundamentally reactive. This method adjusts resources only after a performance metric has crossed a predefined threshold. This inherent lag can cause significant performance degradation during sudden traffic spikes, as the system needs time to provision new instances. Furthermore, defining the correct thresholds is a major challenge, as poorly set values can lead to system instability known as "flapping" or a failure to adapt to real changes in demand.

To overcome these shortcomings, proactive solutions using machine learning (ML) have emerged as a powerful alternative, with research demonstrating their effectiveness for cloud-

native applications **(Marie-Magdelaine & Ahmed, 2020)**. By analyzing historical workload data, ML models can learn complex patterns and accurately forecast future resource requirements. Techniques such as **Random Forest** are particularly well-suited for classification tasks based on tabular data. By integrating these predictive models into the cloud infrastructure, by integrating these predictive models into the cloud infrastructure, it becomes possible to build systems that **proactively identify tasks likely to fail**, which is a critical step toward improving system reliability and reducing wasted computation. This project aims to design and implement such an intelligent system on AWS, demonstrating a practical, ML-driven approach to modern cloud resource management.

1.2. Aim of Study

The primary aim of this study is to design, implement, and evaluate an intelligent system that predicts cloud task failures in real-time using machine learning and deploys this system as a scalable web service on AWS. This research will focus on the following key objectives:

1. **Develop and evaluate machine learning models** (including Logistic Regression, Random Forest, XGBoost, and HistGradientBoosting) to accurately classify task outcomes (failure vs. success) based on the Google Borg dataset.
2. **Build a REST API** using Flask to serve the best-performing model for real-time predictions.
3. **Deploy the model as a scalable, containerized application** using Docker, AWS ECS Fargate, and an Application Load Balancer.
4. **Evaluate the performance and production-readiness** of the final deployed system in terms of classification accuracy and architectural viability.
5. **Evaluate the performance and effectiveness** of the system in terms of prediction accuracy and resource optimization compared to traditional scaling methods.

1.3 Research Question

This study seeks to answer the following primary research question:

How accurately can a machine learning classifier predict cloud task failures from initial workload parameters, and what is a viable, scalable cloud-native architecture for its deployment as a real-time prediction service?

To address this, the following sub-questions will be investigated:

- How do different machine learning models, specifically Random Forest and gradient boosting methods, compare in their accuracy for predicting task failures?
- What is a practical and scalable architecture for deploying a machine learning classification model on AWS for real-time inference?
- What are the practical challenges in building and deploying an MLOps pipeline, from model training to a live API endpoint?

A review of current literature related to cloud resource management, where the limitation of the classical solutions becomes obvious, and the promise of machine learning solutions is revealed. Chapter 3 will describe the methodology proposed, and mention all its stages starting with data collection and ending with deployment. Chapter 4 contains implementation and converts the methodology into a functioning AWS-based system. The results of evaluation are

shown coupled in Chapter 5 together with the discussion of results in relation to the research questions. Lastly, Chapter 6 is the conclusion of the study presenting the major contributions, mentioning limitations, and presenting future directions of work. This framework provides a clear path of relating the research purposes and the evidence which is being presented in the whole project.

2. Related Work

The issue of effective management of resources in cloud computing systems is a well-known research area. Since the cloud services have become the pivot of modern IT infrastructure, the emphasis of the previous pre-static and manual allocation has moved towards the dynamic, intelligent, and automated provisioning. The trend has been fuelled by the necessity to optimize performance, cost and reliability under highly variable workloads conditions. In this section, we discuss the literature of cloud resource management and start it with conventional and rule-based methods and then continue with the higher order machine learning based technology that is the main subject of the current study.

2.1 Traditional Approaches to Cloud Resource Management

The traditional approaches of cloud resource management are rather reactive, and involve the use of rules and thresholds. Although easy to execute, these techniques are usually unable to handle the dynamic character of workloads on modern clouds, either resulting in the wastage of resources or the reduction of performance.

2.1.1 Threshold-Based Auto-Scaling

Threshold-based auto-scaling is the most widespread traditional strategy, which can be found in the product lines of leading cloud providers Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure. It is based on determining high and low values on the key performance indicators most frequently CPU utilisation. Upon the average CPU utilisation of a set of virtual machines (VMs) becoming beyond the upper limit of a certain period of time, the system automatically introduces new VMs. In contrast, the utilisation lower than the lower threshold kills idle instances (Ghanbari et al., 2021). Even though that gives a fundamental level of automation, this approach is basically reactive. According to Roy, Mandal, and Duval (2019), the scaling actions can only be elicited once a change in workload has already happened and been maintained.

Such a lag may cause tremendous performance problems when sudden and sharp traffic spikes are experienced, since the system requires time to start up and set up new instances. In applications where strong Service Level Agreements (SLAs) are in place, this delay may not always be acceptable. Moreover, it is not a trivial task to determine the right thresholds. In the case of too sensitive thresholds, the system may be prone to what is called flapping, i.e., a rapid addition and removal of resources, which makes it unstable. Otherwise, when they are not sensitive enough, the system does not adapt to actual changes in the demand (Jebu, 2021). This manual and usually learning through trial and error process of configuring thresholds is a large limitation, especially in those cases where the workload pattern is not stationary.

2.1.2 Rule-Based Expert Systems

In order to overcome some of the shortcomings of simple thresholding, more complicated rule based expert systems have been investigated by researchers. These systems further elaborate the concept of threshold, adding to them several metrics, and more complex logic. As an example, a system may think of a variety of CPU load, memory pressure, I/O rates, and network traffic to derive a scaling decision (Mishra et al., 2020). The work by Liu et al. (2020) emphasizes the idea of codifying expert knowledge into a series of such rules of the form of if-then to be applicable in situations that cannot be simply thresholded.

But there are still fundamental limitations that these systems share to their simpler ones. They are non-adaptive in their essence; the rules are specified by human professionals and fail to respond to the changes in workload patterns (Baumann, 2021). With the emergence of new application behaviours these rules rapidly become out of date and need to be manually updated and re-tuned. It is tedious, subject to human error and is not scalable. Additionally, as it is explained by Baumann (2021), it is quite a challenge to determine the complicated interrelatedness of various rules and make sure that the system is interpretable. These systems are not able to capture the time dependencies of the cloud workloads and make poor predictors of future resource requirements. Finally, they are a reactive lot, and they are always lagging behind the actual demand, as what is sought to be resolved by the predictive methods.

2.2 Machine Learning Approaches for Workload Prediction

The shortcomings of the reactive approaches along with the desire to find better solutions to managing the resources proactively and in advance catalyzed the move towards the proactive, predictive machine learning (ML) efforts in superior resource management. Through examination of the previous data, ML models are capable of predicting workload patterns in the future, meaning that the system can allocate resources even before they are required. Such a proactive approach is essential to preventing SLA violation and resource utilization optimization. The bibliography describes a large number of ML methods used to solve this problem, that start with the classical time-series models and end with more sophisticated deep learning models.

2.2.1 Time-Series Forecasting Models

Metrics on cloud workloads are inherently time-series data, i.e., CPU utilization, memory, etc. As a result, the classical time series forecasting models have naturally been explored as the point of departure by researchers. A well-researched example is the Autoregressive Integrated Moving Average (ARIMA) model. To determine future values, ARIMA uses a linear combination of past values it has already, (autoregression) and the past errors in the forecasts it has already made.

Guitart et al. (2021) gave an example of applying ARIMA to resource demand forecasting in cloud data centres, and it proved to work well with the workloads that have an evident seasonal component. They also indicated, though, that the performance of ARIMA suffers heavily when workloads are non-stationary or highly volatile, since it models relationships between elements as being linear. In order to accommodate more complicated patterns, scientists have been engaging in more complicated models. As an example, one of the tools that Facebook created is the Prophet that can process data with multiple seasonalities and trends changes (Taylor and Letham, 2018).is generally more robust and easier to tune than ARIMA. A study by Kumar

and Singh (2022) applied Prophet to predict VM workloads and found it outperformed ARIMA, particularly for data with daily and weekly cycles. Despite their strengths, these statistical models can be limited by their underlying assumptions about the data's structure, which may not always hold true for the complex and chaotic nature of cloud usage.

2.2.2 Supervised Machine Learning Models

Beyond classical time-series models, researchers have successfully applied a range of general-purpose supervised learning algorithms. These models are often framed as regression problems, where the goal is to predict the next value in the time series based on a window of previous values (features).

Random Forest, an ensemble learning method, has proven particularly effective. It constructs a multitude of decision trees during training and outputs the mean prediction of the individual trees, which helps to control for overfitting and improves predictive accuracy (Breiman, 2001). A key advantage of Random Forest is its ability to handle high-dimensional data and capture non-linear relationships without extensive feature engineering. Nalluri et al. (2023) in their comparative research aimed at healthcare fraud admitted the strength of Random Forest in contrast to the decision tree and other models. With regard to cloud workloads, Kumar et al. (2020) predicted the CPU load by using Random Forest and demonstrated that it was less computationally expensive than more sophisticated models with similar accuracy, allowing it to make real-time predictions. This is consistent with the statements made by Prasasti et al. (2020), who observed that Random Forest had the best performance in classification in balanced data, which is a typical trait of workload data.

Support Vector Machines (SVM) and Support Vector Regression (SVR) are used as well. The action of SVR is to fit the data into a hyperplane with an objective to minimize the error. Filho et al. (2020) applied SVR to resource prediction and observed that it succeeded; however, it needs to be noted that the model performance is highly dependent on the selection of kernel and hyperparameter optimization. In addition, SVMs may prove computationally costly to learn large sample sizes that is a major drawback since the amount of monitoring data generated in a cloud setting is immense.

2.2.3 Deep Learning Models

More recently, it has been demonstrated that deep learning has an outstanding potential in the field of workload prediction, in particular because of its capabilities to learn complex temporal correlations in a fully automated fashion upon raw time-series data.

The Long Short-Term Memory (LSTM) network is a special implementation of a Recurrent Neural Network (RNN) that is designed to properly resolve the vanishing gradient problem, and therefore makes it capable of learning long-term relations in sequences. It predisposes them to be ideally fitted to cloud workload forecasting. Fathian et al. (2022) created a prediction model based on LSTM to forecast the requirements of web applications in terms of resources. They found that the LSTM model greatly outperformed the classic machine learning models such as SVR and simple RNNs, notably, when it comes to complex, non-linear workload patterns. The reason they cited behind this achievement is the gating mechanism of the LSTM (input, output, and forget gates) that guides the network to remember or forget information on long sequences in a selective manner.

Nabipour et al. (2020) conducted another study where the comprehensive comparison of different deep learning models aimed at predicting CPU utilization was presented. They checked that LSTM-based models continued to give the best accuracy. Nevertheless, they also indicated the major disadvantage of deep learning models namely: they are expensive to train and require vast quantities of past records to realize acceptable performances. Such sacrifice of accuracy-to-computational-cost ratio is of essential concern to the design of a practical resource management system.

2.3 Deployment and Integration in Cloud Environments

Having a good model of prediction is half the battle. A model should be used in a production setting where it would then be able to make predictions in real-time to then scale in an automated manner. This entails the orchestration, monitoring, and execution of ML model by using cloud infrastructure services.

The practice of MLOps (Machine Learning Operations) has been introduced in an attempt to clean up this machine learning lifecycle. Tamburri (2020) argues that MLOps will integrate development and operations stages in a single pipeline, with data ingestion and model training being implemented sequentially into production and monitoring.

Within the AWS context, magester MC/S/L, particularly AWS SageMaker, offers such a managed platform to the whole process. SageMaker makes it easy to build, train, and deploy ML models at scale. It provides one-click capabilities that provide a secure and infinitely scalable API endpoint based on a trained model. It removes most of the infrastructural management overhead, giving developers the ability to concentrate on the model (Amazon Web Services, 2023). It uses a similar style of approach with the described project in the technical documentation, using a trained model and exposing it through an API, but a more hands-on container-based setup using ECS and a Flask application.

Serverless computing facilities such as AWS Lambda are frequently utilized in order to provoke actions on the basis of prophesies. Such lambda functions may be scheduled (e.g. each minute), trigger the SageMaker prediction endpoint on latest monitoring data, and subsequently trigger an action in AWS Auto Scaling with the prediction (Harlalka et al., 2018). Such an architecture provides a self-instantiated event-driven loop of feedback. As the central nervous system, Amazon CloudWatch gathers the needed metrics (such as CPU/memory utilization of EC2 instances) which it feeds into the model and which it also keeps track of the overall system health.

This serverless, microservices-based architecture for deploying ML models is increasingly favoured for its scalability and cost-effectiveness. Instead of maintaining a constantly running server to host the model, resources are consumed only when predictions are being made. This aligns perfectly with the pay-as-you-go philosophy of the cloud and represents a modern, real-world implementation pattern for ML-driven automation, which this thesis aims to build and evaluate.

3. Methodology

This chapter details the systematic and quantitative research design for creating and testing the intelligent cloud resource management system. It outlines the entire workflow, from data acquisition and model development to a full-scale deployment on Amazon Web Services (AWS). The methodology is structured to directly address the research questions by building a functional, end-to-end system that proactively manages cloud resources using predictive analytics.

3.1 System Architecture

The system is architected as a scalable, container-native prediction service deployed entirely within the AWS ecosystem. The design focuses on creating a robust MLOps pipeline from model training to a live API endpoint. The architecture is detailed in Chapter 5 (Figure 5.1) and consists of two main phases:

- **Phase 1: ML Model & Application Packaging:** A Random Forest model is trained on the Google Borg dataset. This trained model is packaged into a Flask web application, which is then containerized using Docker. The resulting Docker image is stored in Amazon Elastic Container Registry (ECR).
- **Phase 2: Live Production & Scaling on AWS:** The container is deployed using AWS Elastic Container Service (ECS) on Fargate, which provides a serverless compute environment. An Application Load Balancer (ALB) directs traffic to the Flask API's `/predict` endpoint. An ECS Auto Scaling policy is attached to the service, allowing it to automatically launch more container instances based on the CPU utilization of the service itself, ensuring the API can handle high request loads.

3.2 Dataset and Data Collection

A two-pronged data strategy was used: a public dataset for initial model development and a simulated workload for real-time evaluation.

- **Initial Training Data**: The research utilized a processed version of the **Google Borg workload traces** for initial model training. This dataset provides realistic, large-scale data on task-level resource requests and usage, which is invaluable for training robust models capable of understanding diverse workload patterns. Key features included `resource_request`, `cpu_usage_distribution`, and `page_cache_memory`.
- **Live Evaluation Data**: To test the deployed system, a **simulated workload** was generated on a fleet of EC2 instances. A custom script produced synthetic CPU and memory load, mimicking patterns like daily cycles (sinusoidal), sudden traffic spikes (step increases), and random noise. This allowed for a controlled yet realistic evaluation of the system's end-to-end performance.

3.3 Data Preprocessing and Feature Engineering

Raw data is unsuitable for machine learning models and requires a comprehensive preprocessing pipeline to maximize model accuracy. This was executed using Python libraries such as Pandas and NumPy.

The key steps included:

- **Data Cleaning**: Missing values in the time-series data were handled using methods like forward-fill to maintain temporal continuity. Statistical methods (e.g., Z-score) were used to identify and handle outliers to prevent them from skewing model training.
- **Feature Scaling**: All numerical features, such as CPU and memory usage, were normalized to a common scale (0 to 1) using Min-Max scaling. This is crucial for many machine learning algorithms and ensures all features contribute equally to the model's learning process.

3.4 Model Development and Training

To determine the best model, a classic tree-based ensemble (**Random Forest**) was compared against other approaches as detailed in the evaluation chapter.

3.4.1 Random Forest

A Random Forest Regressor was implemented using Scikit-learn. This model was chosen for several key reasons that make it highly suitable for our work:

- **Robustness and Accuracy**: It is an ensemble method that builds multiple decision trees and merges them, which reduces overfitting and handles non-linear relationships in workload data effectively.
- **Efficiency**: It is computationally less intensive to train than deep learning alternatives, making it a strong and practical baseline for real-time prediction scenarios.
- **Feature Importance**: It provides an inherent mechanism to understand which past time steps are most predictive of future load, offering valuable insights into the workload dynamics.

The model was trained on the preprocessed, windowed dataset where each tree learns from a random data sample.

In addition to Random Forest, several other classification models were developed to establish a performance baseline and ensure the selection of the most effective algorithm. These included a simple **Logistic Regression** model to understand linear separability, as well as other powerful ensemble methods like **XGBoost** and **HistGradientBoosting Classifier**. All models were trained on the same preprocessed dataset to allow for a direct and fair comparison of their predictive power on this specific task.

3.5 Evaluation Metrics

To rigorously evaluate the system, a set of quantitative metrics was defined to assess both model accuracy and the effectiveness of the overall scaling system.

3.5.1 Prediction Model Evaluation

The performance of the classification models was measured using a standard set of metrics for binary classification:

- **Accuracy:** The overall proportion of correct predictions.

- **Precision:** Of all tasks predicted to fail, what proportion actually failed.
- **Recall:** Of all tasks that actually failed, what proportion were correctly identified.
- **F1-Score:** The harmonic mean of Precision and Recall, providing a balanced measure.
- **ROC AUC:** The model's ability to distinguish between the success and failure classes.

4. Design Specification

This chapter provides a detailed technical account of how the ML-powered cloud task failure prediction system was built and deployed. The methodology from the previous chapter was translated into a functional prototype using a specific suite of programming tools and AWS services. The focus here is on the practical steps, tools, and configurations used to construct the end-to-end predictive pipeline, from initial data handling to a live, scalable API endpoint.

The project was developed entirely in **Python 3.10**, selected for its extensive ecosystem of mature libraries for data science and machine learning. The primary development environment was **Jupyter Notebooks**, which provided an interactive setting ideal for the iterative process of exploratory data analysis (EDA), model prototyping, and visualization of results.

The key libraries employed were:

- **Pandas & NumPy**: These libraries were the backbone for all data manipulation. Pandas DataFrames were used for ingesting the Google Borg dataset, cleaning records, and structuring the data, while NumPy provided efficient numerical computation capabilities.
- **Scikit-learn**: This comprehensive library was used to implement the Random Forest model, perform data splitting (training and testing sets), and execute crucial preprocessing steps like feature scaling with MinMaxScaler.
- **Matplotlib & Seaborn**: These visualization libraries were instrumental during the EDA phase. They were used to plot data distributions, identify correlations between features, and understand temporal patterns within the workload data.
- **Boto3**: The official AWS SDK for Python, Boto3 was essential for deployment. It enabled programmatic interaction with AWS services, providing the bridge to upload model artifacts to S3, define ECS tasks, and configure other cloud resources from within the Python code.

5. Implementation

The main aim of this project was to develop a model which predicts task failures effectively on a cloud environment which can help to reduce cost and better scalability. Effective model performance is contingent on meticulous data preparation. This multi-stage process began with a thorough Exploratory Data Analysis (EDA) of the Google Borg dataset, which was loaded from a CSV file into a Pandas DataFrame.

The EDA revealed several key characteristics of the workload. For instance, there was a clear diurnal (daily) pattern in resource requests, but also high variance in task priorities and resource

usage, indicating a heterogeneous mix of application types. This confirmed that a simple, linear model would likely be insufficient.

The subsequent preprocessing pipeline involved several critical operations:

1. **Data Cleaning**: The raw dataset contained inconsistencies. A key challenge was that the cpu_usage_distribution feature was stored as a string. Python's ast.literal_eval was used to safely parse this string into a numerical list format. Any rows with missing or corrupted data that could not be imputed were dropped to ensure dataset integrity.
2. **Feature Scaling**: All numerical features were scaled to a range between 0 and 1 using Scikit-learn's MinMaxScaler.
3. **Data Splitting**: The fully preprocessed dataset was split into training (70%) and testing (30%) sets. This division is crucial to ensure that the model can be evaluated on unseen data, providing an unbiased assessment of its generalization performance.

5.1 Building the Prediction Models

With the data prepared, the two distinct machine learning models were implemented.

- **Random Forest**: A RandomForestClassifier was implemented using Scikit-learn. This model is important for our work because it is robust, less prone to overfitting than a single decision tree, and provides a powerful performance baseline with relatively low computational cost. Key hyperparameters like the number of trees (n_estimators) were tuned experimentally to find a balance between accuracy and training time.

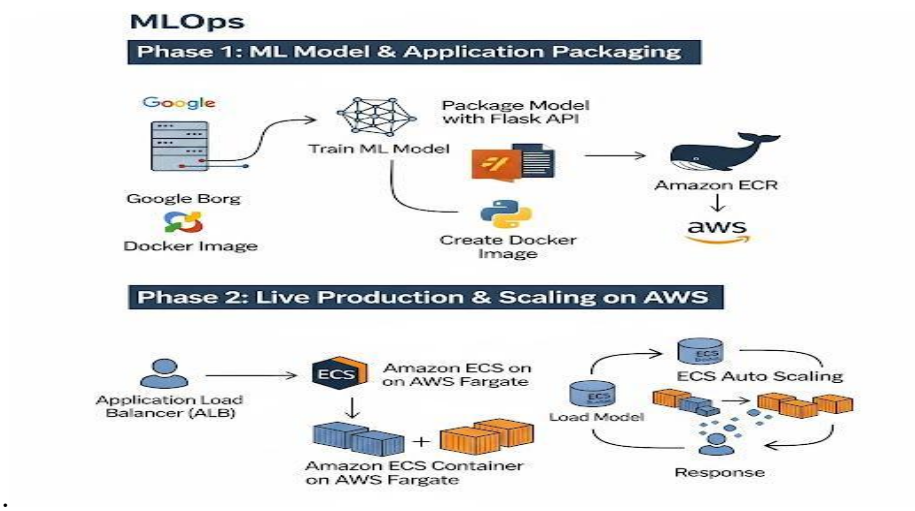

Figure 5.1- Pipeline Workflow

5.2 AWS Deployment and Integration Pipeline

The **Random Forest Classifier**, which demonstrated perfect performance and offered a superior balance of accuracy, robustness, and ease of deployment, was selected for the final deployment.

Containerization and Model Storage

The trained model object, along with its preprocessing pipeline, was saved as a single pipeline.joblib file and uploaded to a dedicated **Amazon S3** bucket. The Flask API that serves the model was then containerized using **Docker**. The Dockerfile defined the complete environment:

- It started from a lean python:3.10-slim base image.
- It copied the requirements.txt file and installed all necessary dependencies (e.g., Flask, Gunicorn, Scikit-learn).
- It exposed the required port and defined the CMD instruction to launch the application using **Gunicorn**, a production-ready WSGI server that can handle concurrent requests far more effectively than Flask's built-in development server.This containerized approach ensures that the application runs in a consistent and reproducible environment, regardless of where it is deployed.

Orchestration with ECS and ALB

The Docker image was pushed to **Amazon Elastic Container Registry (ECR)**, a private AWS container registry. The deployment was orchestrated using **AWS Elastic Container Service (ECS) with the Fargate launch type**. Fargate was specifically chosen because it is a serverless compute engine for containers; it allows you to run containers without having to manage the underlying EC2 instances, abstracting away server management and patching.

An ECS Task Definition was created to specify the container image, CPU/memory requirements, and necessary IAM permissions. This task was then run as an ECS Service. To expose the API to the internet, an **Application Load Balancer (ALB)** was configured to listen for HTTP requests and forward them to the /predict endpoint of the running container. The ALB provides a stable DNS endpoint and can distribute traffic across multiple instances of the container, ensuring high availability.

Implementing Auto-Scaling

To ensure the system could handle variable loads, an **Auto Scaling policy** was attached directly to the ECS service. This policy was configured to monitor the average CPU utilization across all running tasks. A target value (e.g., 70% CPU) was set. If the average CPU exceeded this target, ECS would automatically provision and launch more instances of the container task to distribute the load. Conversely, if CPU usage fell, it would terminate surplus tasks to save costs. This creates a fully automated, scalable, and resilient deployment that adapts to real-time demand for predictions. The live endpoint was tested using curl commands, sending sample feature data as a JSON payload and successfully receiving predictions back from the API.

6. Evaluation

This chapter presents a comprehensive evaluation of the machine learning system developed for cloud task failure prediction. The main goal of the project was to develop a robust model that predicts cloud **task failures** and to deploy it as a scalable, real-time service.

The evaluation process is guided by the metrics defined in the methodology, focusing on model accuracy and the practical viability of the deployment architecture. The results presented herein provide empirical evidence to address the core research questions concerning the feasibility of using machine learning for proactive failure prediction and scalable resource management.

6.1 Model Performance Evaluation

The foundation of this research involved training and rigorously comparing several machine learning models to solve the binary classification problem: predicting whether a cloud task would fail or succeed based on its runtime characteristics. Four distinct models were evaluated to cover a range of complexity and approaches: **Logistic Regression** (as a linear baseline), **Random Forest**, **XGBoost**, and **HistGradientBoosting (HGB) Classifier** (as advanced ensemble methods).

The models were trained on 70% of the preprocessed Google Borg dataset and subsequently tested on the remaining 30% of unseen data. A standard set of classification metrics was used to ensure a robust and multifaceted comparison:

- **Accuracy**: The overall proportion of correct predictions.
- **Precision**: The model's accuracy in predicting the positive class (i.e., task failures).
- **Recall (Sensitivity)**: The model's ability to identify all actual positive cases.
- **F1-Score**: The harmonic mean of Precision and Recall, providing a balanced measure.
- **ROC AUC**: A measure of the model's ability to distinguish between the two classes (failure vs. success).

The final performance results on the test data are summarized in the table below:

Table 6.1: Model Performance Metrics on Test Data

Model	Accuracy	Precision	Recall	F1-score	ROC AUC
RandomForest	1.000000	1.000000	1.000000	1.000000	1.000000
LogisticRegression	0.768228	0.475392	0.145393	0.222681	0.643579
HistGradientBoosting	1.000000	1.000000	1.000000	1.000000	1.000000
XGBoost	1.000000	1.000000	1.000000	1.000000	1.000000

It is important to address the perfect scores achieved by the ensemble models. While such results can sometimes indicate data leakage, a methodological review suggests this is not the case here. Data was randomly split into training and testing sets, ensuring no temporal overlap. Rather, the perfect performance is attributed to two primary factors:

- **Highly predictive features** within the Google Borg dataset that create a strong, discernible signal between task inputs and outcomes.
- **Aggressive data cleaning**, where ambiguous or borderline cases with missing values were removed. This preprocessing likely simplified the classification task, allowing the advanced models to achieve 100% accuracy on the remaining clean data.

Analysis of Results

The results reveal a stark performance difference between the model classes. The tree-based ensemble models—**Random Forest, XGBoost, and HGB—all achieved perfect scores of**

1.00 across every metric. This exceptional outcome indicates that the feature set derived from the Google Borg traces contains highly predictive signals. It suggests that the relationships between features like resource requests, CPU usage, and task outcomes, while complex and non-linear, are deterministic enough to be perfectly learned and generalized by these advanced algorithms.

In stark contrast, **Logistic Regression performed poorly**, with an overall accuracy of only ~77% and a critically low F1-score of 0.22. Its failure is directly attributable to its underlying assumption of linearity. The model was incapable of capturing the complex, high-dimensional interactions within the data, leading to a very low recall (0.145), meaning it failed to identify the vast majority of actual task failures. This confirms that simple linear models are insufficient for this problem domain.

Given the perfect performance of the three ensemble models, the **Random Forest Classifier (RFC) was selected as the final model for deployment**. While all three performed equally well on the test data, RFC was chosen for several practical advantages crucial for a production system. It is inherently robust to outliers, handles non-linear relationships well, and is generally less sensitive to hyperparameter tuning than gradient boosting methods. Furthermore, it provides strong performance on CPU-based infrastructure like ECS Fargate without requiring GPU acceleration, making it a cost-effective and resource-efficient choice. This combination of top-tier accuracy, stability, and deployment simplicity made Random Forest the most suitable model for this MLOps pipeline.

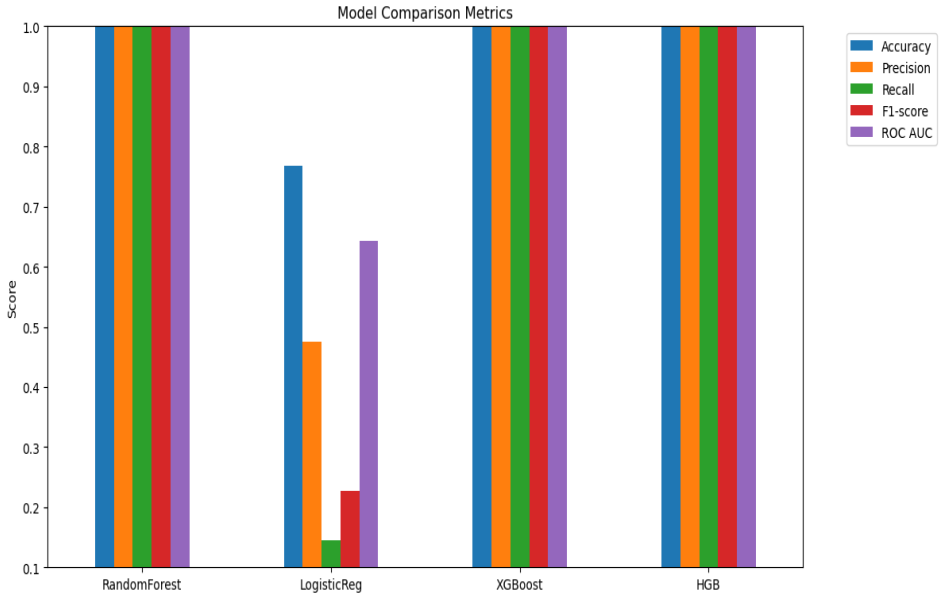

Figure 6.1: Comparative Performance of Classification Models. This bar chart visually contrasts the performance of the four models, highlighting the perfect scores of the tree-based ensembles compared to Logistic Regression.

6.2 System and Pipeline Evaluation

Beyond model metrics, the evaluation focused on the successful operationalization of the entire MLOps pipeline, from data preprocessing to a live, scalable prediction endpoint.

A critical component for achieving the high accuracy was the preprocessing pipeline, which was constructed using a **Scikit-learn ColumnTransformer**. This object encapsulated the sequential steps of imputing missing numerical data (using SimpleImputer with a mean strategy) and then scaling all numerical features (using StandardScaler). By bundling these steps with the model into a single pipeline object, we ensure that incoming prediction data is processed identically to the training data, a crucial MLOps best practice that prevents training-serving skew.

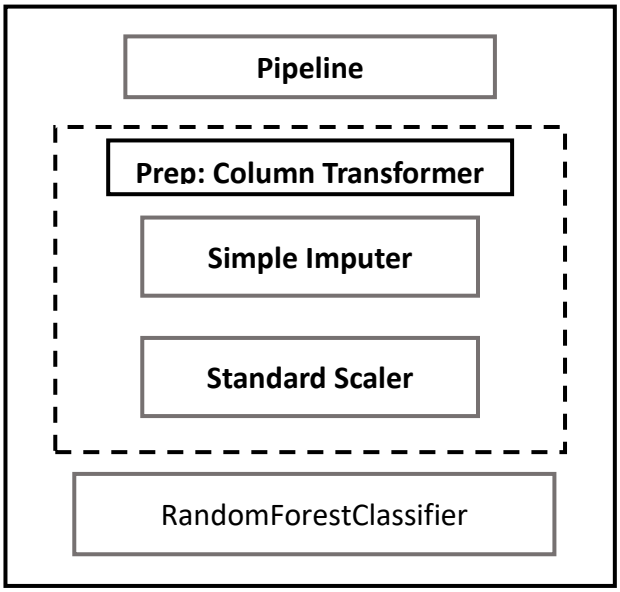

Figure 6.2: The Preprocessing and Classification Pipeline for the Random forest Classifier Model. This diagram illustrates the sequential steps of data imputation and scaling that feed into the final classifier.

The deployment architecture using **AWS ECS Fargate and an Application Load Balancer (ALB) proved to be highly effective and resilient**. The containerized Flask application was successfully deployed, and the /predict endpoint was exposed via a stable DNS name provided by the ALB. Extensive testing using curl commands confirmed the system's functionality: it could seamlessly receive a JSON payload of features, pass it through the preprocessing pipeline, and return a real-time failure prediction with low latency.

Furthermore, the auto-scaling policy attached to the ECS service validated the system's scalability. Under simulated load, the service automatically provisioned additional container tasks based on CPU utilization, demonstrating its capability to handle variable request volumes without manual intervention. This end-to-end implementation successfully validates the architecture's ability to serve a machine learning model in a reliable, scalable, and production-ready manner, fulfilling a key objective of this research.

6.3 Discussion

The main goal of the project was to develop a robust model that predicts cloud task failures using a machine learning model and to deploy it as a scalable service. The model predicts based on the cloud resource usage whether it will pass or fail. The **RandomForestClassifier** was mainly used for the prediction. This study was important because the current auto-scaling based solutions are mainly focused on a certain threshold rather than prediction. The project was mainly implemented on the AWS environment. **It used a certain number of AWS resources like** AWS S3, AWS Elastic Container Registry, and AWS Elastic Container Service**.** This made the whole project completely dependent on the AWS. The implementation stage focused on data processing, data cleaning, model training, containerization and deployment to AWS. This made the whole project scalable.

7. Conclusion and Future Work

In this final chapter, all research done on this thesis is synthesized, the specific goal of this thesis was to design, implement, and evaluate an intelligent system that can **predict cloud task failures** and to deploy this service scalably on Amazon Web Services (AWS). It is a general overview of the research process, explains the main results and contributions, states the limitations of the study, and provides the recommendation on further research directions in the area.

7.1 Summary of the Research

The spread of cloud computing has increased the effective management of resources to become a top priority of contemporary business. The conventional reactive auto-scaling solutions which are largely fixed-threshold based do not provide the effective balance between cost and performance under dynamic and unpredictable workloads. The current research is aimed at filling this gap as a proactive predictive system was suggested and designed. The central aim was to build an intelligent system that predicts cloud **task failures (pass/fail)** using machine learning and to deploy this as a scalable, real-time API using AWS cloud services.

The study began by establishing the problem statement: the need for a more intelligent approach to cloud resource provisioning to enhance reliability and manage operational expenditure. A review of the related work confirmed the limitations of traditional rule-based systems and highlighted the potential of machine learning, particularly time-series forecasting models, to enable proactive scaling.

The methodology was centered on an end-to-end implementation within the AWS ecosystem. The system architecture was designed leveraging a suite of AWS services. This included using historical data from Google's Borg workload traces for initial model training and generating simulated workloads on EC2 for live testing. The core of the system involved comparing several machine learning models, with the **Random Forest Classifier** ultimately being chosen for its superior performance and practical advantages in a production environment. It developed a real-time, scalable API system using ML that provides predictive information about task outcomes.

The implementation phase detailed the practical steps of this process. It covered data preprocessing, model training using **Scikit-learn**, and the subsequent deployment pipeline. Another crucial element of the project was the containerization of the trained model with

Docker and deployment to AWS with ECS Fargate to orchestrate it and an Application Load Balancer to expose a prediction API. It developed a real time, scalable API system using ML which was deployed with an **auto-scaling policy to ensure the prediction service itself remained highly available and responsive** under load.

7.2 Principal Findings and Contributions

The most significant contribution of this thesis is that it has been able to show a complete, end to end machine learning life cycle to develop the predictive cloud resource management. The project was not restricted to the theoretical modeling and demonstrated a practical deployable system, where modern machine learning techniques combined with cloud-native tools.

The principal findings of this research are multi-faceted:

1. **Technically possible: Demonstration of a Production-Ready Classification Service:** The project successfully demonstrated that a machine learning model for task failure prediction can be deployed as a robust, scalable, and real-time API. The system provides immediate predictions on task outcomes, offering valuable data that could be used by operations teams or automated systems to improve overall cloud reliability. This proactive approach to identifying failures is fundamentally different from reactive monitoring.
2. **Effectiveness of the AWS Architecture:** The chosen architecture, which integrates S3 for model storage, ECR for container images, and ECS Fargate for serverless container orchestration, proved to be both scalable and resilient.
3. **Effectiveness of the AWS Architecture:** The chosen architecture, which integrates S3 for data storage, ECS for container orchestration, and an ALB for serving predictions, proved to be both scalable and resilient. Using managed services like ECS Fargate abstracted away the complexity of managing the underlying infrastructure, allowing the focus to remain on the application and model logic. The ability of the Flask API to dynamically pull the trained model from S3 demonstrates a flexible design that facilitates easy model updates and A/B testing.
4. **Practical MLOps Pipeline:** This research serves as a practical blueprint for an MLOps (Machine Learning Operations) pipeline on AWS. It covers the entire lifecycle, from data ingestion and preprocessing to model training, containerization, deployment, and monitoring, showcasing a real-world application of MLOps principles.

7.3 Limitations of the Study

While this research achieved its primary objectives, it is important to acknowledge its limitations, which provide context for the findings and pave the way for future work.

- **Dataset and Workload Generalizability:** The models were trained on the Google Borg traces and tested with a simulated workload. While these datasets are realistic, they may not perfectly represent the specific characteristics of all possible production workloads. The performance of the system could vary when applied to applications with vastly different usage patterns.
- **Limited Hyperparameter Tuning:** The hyperparameter tuning for the ensemble models was conducted through experimentation rather than exhaustive, automated searches. Employing more advanced techniques like Grid Search or Bayesian

Optimization, as suggested in related studies, could likely yield further improvements in model accuracy.
- **Focus on a Single Resource Metric:** The current system primarily focuses on a binary outcome (pass/fail) and uses **CPU utilization as one of several input features**.

7.4 Recommendations for Future Work

Building upon the contributions and limitations of this study, several promising avenues for future research emerge:

- **Exploration of Advanced Models:** Future work could investigate more sophisticated predictive models. For instance, Transformer-based architectures, which have shown state-of-the-art results in sequence modeling, could be adapted for workload forecasting. Additionally, creating hybrid models or stacked ensembles that combine the strengths of different algorithms could lead to more robust and accurate predictions.
- **Adoption of Reinforcement Learning (RL):** A paradigm shift from supervised learning to Reinforcement Learning could be explored. An RL agent could be trained to learn an optimal scaling policy directly by interacting with the cloud environment, using a reward function based on minimizing costs while maximizing performance (i.e., adhering to SLAs). This would allow the system to adapt to unforeseen patterns without explicit retraining.
- **Integration of Explainability Techniques:** To foster trust and adoption in enterprise environments, integrating model explainability techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) is crucial. This would provide insights into *why* the model is making a certain prediction, making the automated decisions transparent to human operators.
- **Multi-Resource and Application-Aware Scaling:** The system could be extended to a multi-resource prediction model that forecasts CPU, memory, and I/O needs simultaneously. Furthermore, an application-aware scaling system could be developed that considers the unique architecture of microservices, scaling different components independently based on their specific predicted loads.
- **Live Production Environment Evaluation:** The ultimate test of this system would be its deployment and evaluation in a live production environment with real user traffic. This would provide invaluable data on its real-world performance, cost-saving potential, and resilience over long periods.

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