Interim Report

Virtual Machine Failure Prediction using Log Analysis for Proactive Fault Tolerance

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Declaration

The interim report is my original work and has not been submitted previously for any examination/evaluation at this or any other university/institute. To the best of my knowledge, it does not contain any material published or written by another person, except as acknowledged in the text.

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This is to certify that this interim report is based on the work of Mr. P. L. W. Senevirathne under my supervision. The interim report has been prepared according to the format stipulated and is of acceptable standard.

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Contents

List of Acronyms

VM Virtual Machine

OS Operating System

VMM Virtual Machine Monitor

PM Physical Machine

AWS Amazon Web Services

GCP Google Cloud Platform

CDC Cloud Data Center

FT Fault Tolerance

SLA Service Level Agreement

ML Machine Learning

CI Continuous Integration

CD Continuous Delivery

CNN Convolutional Neural Network

LSTM Long Short-Term Memory

FNN Feed-forward Neural Network

SVM Support Vector Machine

LR Linear Regression

VNF Virtual Network Function

NFV Network Functions Virtualization

vEPC Virtual Evolved Packet Core

IDS Intrusion Detection System

NLP Natural Language Processing

BERT Bidirectional Encoder Representations from Transformers

DSR Design science research

1 Introduction

A Virtual Machine (VM) can be thought of as a software emulation of a physical computer. This technology allows several Operating Systems (OSs) to run on a single computer/server, each with its own virtualized hardware, and each VM functions separately from the other VMs in the same Physical Machine (PM). VMs are used for a variety of purposes, including testing and development, application deployment, building Continuous Integration (CI)/Continuous Delivery (CD) pipelines, server consolidation, running legacy applications, etc. They are managed by the hypervisor which is also known as a Virtual Machine Monitor (VMM), a piece of software that creates and manages VMs.

As with any system, VMs are failure prone. VM failures may occur at any moment of its execution or during migration from one host (PM) to another. VM failure can be seen as a failure in the end-user application/service running in the VM. An end-user application/service may experience a failure when there is a failure or an error in the PM (host) hardware components, network, or in software components such as the host OS, hypervisor, VM instance, the guest OS running in the VM, or due to a failure in the end-user application itself (Jhawar and Piuri 2012).

VM failure can cause downtime, loss of user data, and disrupt service availability, leading to negative impacts on users and business operations. By utilizing failure prediction and proactive VM migration techniques, we can greatly reduce service downtime due to VM failures. One effective approach for proactive VM migration is live migration, which enables VMs to be migrated to a healthy PM while maintaining service continuity (Engelmann et al. 2009; Polze, Tröger, and Salfner 2011).

All of the above-mentioned software components related to VMs generate logs that contain valuable information about systems' states and events, including fault and failure data. Using Machine Learning (ML) techniques to analyze these logs, it is possible to predict VM failures and proactively migrate VMs from faulty PMs to healthy ones before the failure occurs (Nam, J. Hong, et al. 2021).

1.1 Background

1.1.1 Virtual Machine Live Migration

The live migration technique tries to migrate the VM while it is switched on, and the applications are still running in them with minimal interruptions to the running applications (Clark et al. 2005). The main objectives of this approach are to optimize the end-user application performance and to minimize downtime. There are three sub-categories, Pre-copy migration, Post-copy migration, and hybrid approach. Figure 1 illustrates the timeline of pre-copy vs post-copy methods.

1. **Pre-copy:**

   A pre-copy migration scheme will migrate the VM from a probable failing node to a target node by iteratively copying all of its memory content before

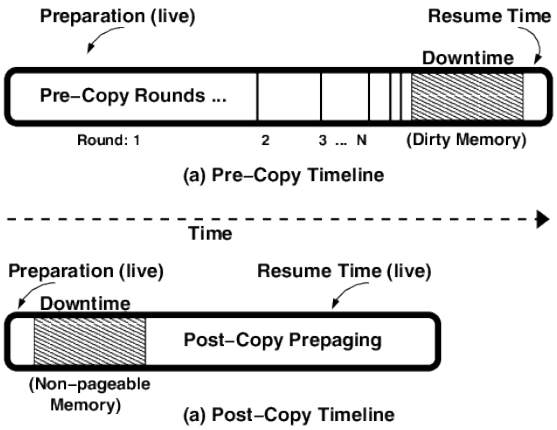


Figure 1: Pre-copy vs Post-copy timeline (M. Hines and Gopalan 2009)

stopping it in the source node and activating it in the target node. This migration scheme is resource intensive and the total migration time is also comparatively high (Shribman and Hudzia 2013).

2. **Post-copy:**

   This scheme will migrate the VM from the host node to the target node by immediately suspending the VM and capturing the minimum possible state to migrate the VM. This is then moved to the target, and the VM is started in the target, and if the guest OS requires a page to read/write which is not already copied, the migration system will copy it to the VMs memory on the fly, over the network. When all the pages are copied from the source server, the connection to the server will be terminated and the source VM can then be terminated (M. R. Hines, Deshpande, and Gopalan 2009).

3. **Hybrid approach:**

   These frameworks integrate the properties of both the previous methods to reduce migration time and improve system performance. It includes a finite pre-copy stage before moving on to migrating the VM and running the post-copy stage. This greatly reduces the page faults that may occur in the future as a large amount of the memory is already copied, so this method reduces the workload on the network and improves the application performance(R. W. Ahmad et al. 2015).

All the existing VM migration schemes can be classified mainly into two groups, namely, proactive migration and reactive migration (R. W. Ahmad et al. 2015; Polze, Tröger, and Salfner 2011).

Reactive Virtual Machine Migration: This method is the most widely adopted and used method in cloud VM Fault Tolerance (FT). Reactive migration deal with faults after they have happened, that is, they migrate the VM to a suitable destination node after a fault/failure has been detected. Using this method will take some time to get the failed VM properly running back again, which may lead to Service Level Agreement (SLA) violation. Even though this method is

undesirable, one advantage of this method is that the overhead associated with running a machine learning algorithm to predict fault occurrence is completely avoided in this mechanism (R. W. Ahmad et al. 2015).

Proactive Virtual Machine Migration: These frameworks continuously monitor the system and predict fault occurrence using an ML or a similar approach and if a VM or the PM is predicted to fail, it will migrate the VM(s) to a chosen healthy PM. This work is focused on proactive migration, where the failure is predicted using an ML approach by analyzing logs.

1.1.2 Logs, Log Keys and Values

Logs are files that contain information about events that occur in a computer system. These events can happen in the OS, in applications, or hardware devices. Logs contain system events, such as startup and shutdown; hardware changes; application events, such as errors, warnings, and performance metrics; security events, such as login attempts, failed access attempts, etc.

The events are logged in the log file as log lines, and the structure of each log file is different. Usually, each log line contains the timestamp at which it was logged, the log verbosity level (INFO, WARNING, SEVERE, etc.), the application information, and the actual log data. The log messages are text printed by logging statements in program code such as *print(), logging.info(), logger.log()* written by the program developers (He et al. 2017).

Following is a small extract from the kernel log file,

```
Sep 12 09:54:45 cloudnet2 kernel: [93248.482863] br0: port 2(tap1)
    entered disabled state
Sep 12 09:54:45 cloudnet2 kernel: [93248.482991] br0: port 4(tap3)
    entered disabled state
Sep 12 12:10:46 cloudnet2 kernel: [ 8132.463411] FS-Cache: Loaded
Sep 12 12:10:46 cloudnet2 kernel: [ 8132.541471] FS-Cache: Netfs 'nfs
    ' registered for caching
```

The unstructured log data needs to be parsed in some way to make them structured, efficient and easier to analyze. In this study, we utilize the log parsing technique, which transforms the log messages into log keys and values. For this, the parser must distinguish the constant and variable parts of each raw log message. The parser assigns a unique ID for each constant part of the log line; this identifier is the log key. The variable part is extracted as the log value(Du, F. Li, et al. 2017; He et al. 2017).

This directly corresponds to the log printing statement in the program source code (Du, F. Li, et al. 2017); for example,

```
printf("%s: port %d(%s) entered %s state", bridgeName, portId,
    portName, portState)
```

The parser outputs parsed log lines as log key and value pairs. Table 1 presents the sample parsed log data output for the above log lines. These values can then be directly used in log analysis.

Parsed log line	Log key	Log values
br0: port ⟨*⟩(tap⟨*⟩) entered ⟨*⟩ state	101	[2, 1, disabled]
br0: port ⟨*⟩(tap⟨*⟩) entered ⟨*⟩ state	101	[4, 3, disabled]
FS-Cache: Loaded	102	[]
FS-Cache: Netfs ⟨*⟩ registered for caching	103	[nfs]

Table 1: Sample Parsed log lines

The pre-processed logs can be used in ML model training, but most of the logs will be assigned to the "normal" class because the VM will not fail under regular operation. Waiting for the VM to fail is not feasible because a VM may not fail in its usual operation and may take months or years to fail under normal conditions. To tackle this issue, we need a way to simulate VM and host failures; fault injection is an effective way of simulating the VM and host failures. During fault injection, we can capture near failure and failure logs (Nam, J. Hong, et al. 2021).

1.1.3 Fault Injection

Fault injection is a software testing technique used to intentionally introduce faults or errors into a system or component to evaluate its behavior and robustness in the presence of unexpected or adverse conditions. The primary purpose of fault injection is to assess how a system responds to faults, errors, or failures and to identify weaknesses in its design or implementation. In this context, we use fault injection software to simulate host and VM failure scenarios. Simulating high resource demands and hardware faults, allows for identifying and collecting near-failure and failure logs. The near-failure logs will contain warning messages, fault logs, and other valuable logs for VM failure prediction.

1.1.4 Machine Learning for Log Analysis

We can utilize several supervised, semi-supervised, and unsupervised ML techniques for log analysis. Recent studies on the subject (Nam, Yoo, and J. W.-K. Hong 2022; Nam, J. Hong, et al. 2021; Jeong et al. 2021), have primarily utilized supervised ML models for failure prediction by analyzing the logs, and they have shown that several ML models prove to be effective, and the authors have shown that Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models have shown superior performance over other models in the reviewed papers.

Some ML models like CNN require the logs to be in a numerical format such as vectors. There are several approaches to achieve this conversion. One common method is to employ word embedding, which involve using a language model to convert log words into tokens and then represent them as vectors. This technique captures the semantic meaning of the words and their relationships within the log

data (Nam, J. Hong, et al. 2021). Alternatively, we can also consider converting the logs to a log event count representation, where each log event is treated as a feature, and the count of occurrences of each event is recorded (Jeong et al. 2021). This study mainly focuses on using the the above-mentioned log key and value representation for this conversion step. These approaches simplify the log data into a numerical format that can be directly used by ML models.

In the Literature Review section, we will discuss how the authors of the related papers have approached this conversion step, and which ML algorithms they have used, providing further insights into their methodologies.

1.2 Motivation

The software industry has widely adopted deploying applications and services on large-scale cloud platforms like Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure in recent years (Bulao 2023). These cloud service systems are required to offer a range of services to millions of users worldwide every day, which makes high service availability crucial, even minor issues can have significant consequences, and many service providers have put in considerable effort to maintain it (Khalili 2020).

Cloud VM is one such service provided by the cloud vendors, and they use several fault tolerance methodologies to keep the VMs up and running most of the time with minimal service downtime. For example, AWS claims to have "five nines" (Reynolds 2020), which means a service availability of 99.999%, allowing at most 26 seconds of downtime per month per VM.

Despite significant effort devoted to quality assurance, cloud service systems continue to face many problems and frequently fail to meet user requests. These problems are often due to computing node (physical server) failures and VM failures within cloud service systems(Lin et al. 2018; Lawrence 2022). Such systems typically comprise a vast number of computing nodes that provide processing, network, and storage resources for VM instances.

Accurate failure prediction will reduce VM downtime significantly, but as identified by Lin et al. (2018), the failure prediction of cloud service systems is extremely challenging due to the following reasons,

Complex causes of node failure: Because of the complexity of the cloud architecture, the node (PM) failure may be caused by different software or hardware issues.

Complicated failure indication: Detection of failure of the node is hard and could be indicated by many signs, and one node failure may affect other nodes to fail due to explicit/implicit dependencies among them.

Highly imbalanced failure data: Node fault/failure data are extremely unbalanced, meaning, most of the data collected by the nodes will be allocated to the healthy class, and failure data are very rare because of the low failure rate of the nodes.

Researchers have attempted to achieve high VM availability by building a node failure prediction algorithm to proactively move the failure-prone VMs to a healthy node using live migration. They have used several strategies to achieve

this while tackling the issues mentioned earlier. Most of them have used physical server (node) resource usage history data to train an ML model to predict the possible future node failure. Even though these papers claim to have achieved successful node failure prediction, they have left out the most crucial part of any digital system that keeps track of the system state and the events, the logs.

VM live migration takes some time, say x minutes, to move a VM from one node to another, so we need a way to reliably predict the VM failure before the time it takes to move the VM to a healthy node. That is, the failure should be predicted x minutes to VM failure. Most of the papers in this area have ignored this basic fact, and even though the failure prediction may be accurate, the VM may fail during migration due to late failure prediction.

Overall, utilizing log analysis and machine learning to predict VM failures *before the time* it takes to migrate the VM and proactively migrating the VM using the live migration technique is an effective strategy for reducing service downtime and ensuring a seamless user experience.

2 Literature Review

2.1 Physical Machine Failure Prediction

In large-scale cloud computing environments with thousands of physical servers, it is inevitable to encounter frequent server failures. According to the studies by Vishwanath and Nagappan (2010), and Birke et al. (2014), approximately 6-8% of all servers experienced at least one hardware issue during a year. Therefore, accurately predicting PM failures is crucial for ensuring cloud system FT.

Numerous studies have been conducted on this topic, and most researchers have utilized PMs' resource usage history data in combination with ML approaches to predict failure. The system administrators label the collected data to train a suitable supervised ML model to predict the failures. For example, the framework proposed by Guan, Z. Zhang, and Fu (2012) uses an unsupervised failure detection model using an ensemble of Bayesian models, and the found anomalous data get verified and labeled by system administrators. This labeled data is then used to train a random forest model to classify the server resource usage data as failure prone or healthy. The framework proposed by Sun et al. (2019) uses a CNN model to predict the PM failures. A similar framework proposed by Gao, Wang, and Shen (2020) uses a Bi-directional LSTM model.

One notable framework that stands out from the rest is the MING framework, developed by Lin et al. (2018) at Microsoft Research. Its successful deployment in a production cloud environment sets MING apart, demonstrating its practicality and effectiveness. MING uses temporal data, such as performance data, log rate, and OS events, and spatial data, such as the server rack location and load-balancer data, to train a LSTM and Random forest models, respectively, to predict the server failure. MING also has a server ranking system, which will rank all the servers from their failure-proneness. Top k servers can then be selected as the faulty servers.

2.2 Virtual Machine Failure Prediction

When it comes to a VM failures, it can be due to either the physical server it is running on or any of the software components involved, such as the host OS, hypervisor, or guest OS. So, physical server failure prediction is a subset of VM failure prediction.

An analysis conducted by Birke et al. (2014) revealed that 60% of the collected VM failure cases were attributed to physical server failures, while the remaining 40% were caused by other factors. One approach to addressing VM failures is the utilization of redundant VMs. For instance, Scales, Nelson, and Venkitachalam (2010) discuss the VMWare VSphere 4.0 VM FT architecture, which employs a redundant VM pattern to replicate the entire execution state of the primary VM through a backup VM on another physical server. Nevertheless, this redundancy strategy can lead to increased costs for cloud service providers, which is not ideal.

An alternative approach involves predicting VM failures and proactively migrating the failure-prone VMs to other physical servers. Similar to the prediction of physical server failures, several studies have focused on VM failure prediction using ML models based on the VM's resource usage history. For instance, Saxena and Singh (2022) conducted a study utilizing an ensemble of predictors using Feed-forward Neural Network (FNN), Support Vector Machine (SVM), and Linear Regression (LR) ML models to identify failure-prone VMs and proactively migrate them to a different host.

Although there is a significant body of research on PM/VM failure prediction utilizing resource usage data, the literature on VM failure prediction using log analysis remains relatively scarce. We will discuss the few papers we found that specifically address this topic, in the Supplementary Details subsection.

2.3 Virtual Machine Live Migration Time Estimation

VM live migration time estimation/prediction is another aspect of successful VM failure prediction because the failure should be predicted before the time it takes to migrate the VM. If not, there will be migration failures or downtime. In this study, we focus on QEMU-KVM live migration, where the VMs' disk images are located on a network file system, and hence, disk image migration is not required.

There are several studies on KVM live migration time estimation/prediction, where most use a statistical method to calculate the estimated migration time. In this work, a statistical approach is preferable over an ML-based prediction technique because of low resource utilization.

Elsaid, Abbas, and Meinel (2022) have conducted a survey on VM live migration cost-modeling, and under section 7 of their paper, they have compared several models for VM migration time estimation. The simplest model they found was t = as+b, where s is the VM memory size, and a and b are constants. This shows that the VM migration time directly depends on the VM memory. However, the study by Nathan, Bellur, and Kulkarni (2015) shows several additional parameters affecting pre-copy migration time, namely, VM memory size, page transfer rate, number of unique pages dirtied during each iteration, and the number of skipped

pages. The memory size and the transfer rate can be predetermined. The other two parameters depend on the application running on the VM. Thus, to accurately predict the migration time of the VM, we may need to use VM resource usage data.

The discussed literature focuses on the pre-copy live migration approach. In most cases, the pre-copy takes longer to migrate a VM when compared to other methods (M. R. Hines, Deshpande, and Gopalan 2009; Shribman and Hudzia 2013). Thus, the above-mentioned migration time prediction method is sufficient for this research.

2.4 Supplementary Details

The framework proposed by Nam, J. Hong, et al. (2021) focuses on predicting the future failure of Virtual Network Functions (VNFs) in a Network Functions Virtualization (NFV) environment built on OpenStack cloud management software (OpenStack 2023). VNF is a VM that runs a network function application such as a firewall or an Intrusion Detection System (IDS). They leverage log data generated by the VNF application and the VM to predict failures. To convert the log data into word embeddings, they employ a Natural Language Processing (NLP) technique using the Google Word2Vec library (Mikolov et al. 2013). A CNN model is then used for failure prediction. The Word2Vec-CNN model achieved an overall F1 score of 0.67, predicting VM failure before 5 minutes of the actual failure.

The authors collected the training log data by using a fault injection method to simulate VM failures. Log data is collected at intervals (m minutes), and labels indicating whether the VM failed are collected after a gap time (n minutes). The trained CNN model predicts VM failure before the gap time. However, the authors observed some unexpected failures with no corresponding failure logs. Therefore, VM failure prediction through log analysis may not cover all possible VM failure scenarios.

In their subsequent work (Nam, Yoo, and J. W.-K. Hong 2022), the same authors improved their approach to predicting VM and PM failures in a similar NFV environment. Instead of Word2Vec, they employed the Google Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al. 2019) for word embedding and a CNN model for prediction. The BERT-CNN model achieved an F1 score of 0.74, predicting server failure 30 minutes before the actual failure. However, the impact of the prediction models on VMs' performance is not mentioned in either paper.

Jeong et al. (2021) proposed a framework to predict paging failure of Virtual Evolved Packet Core (vEPC) in 4G networking. They used VM and server logs and resource usage information to predict VM failure. Unlike the NLP approach in the previous papers, they used the log count (number of occurrences) of specific log types and resource usage data as inputs to an LSTM model for VNF failure prediction. They evaluated the total system throughput with and without the proposed proactive migration system and demonstrated that the framework successfully prevents long-term vEPC failures leading to depleted throughput.

It is important to note that there is a scarcity of research in the area of virtual

machine failure prediction using log analysis, as indicated by the limited number of papers identified during the search. This highlights the need for further research and exploration in this specific field to bridge the existing knowledge gap.

3 Research Gap

The existing studies in the field of VM failure prediction have primarily focused on utilizing physical machine resource usage history and physical component health data to predict failures. However, an important aspect overlooked in these studies is the potential insights provided by VM and PM logs. These logs contain valuable information about VM behaviour, performance, and potential failure indicators, which can significantly enhance failure prediction accuracy.

Previous research on VM failure prediction has only focused on specific types of VMs, such as VNFs, and has not been generalized to generic VMs. This limits the applicability of failure prediction techniques to a broader range of VMs commonly used in cloud computing environments. Additionally, to the best of our knowledge, there are no proactive generic VM failure prediction techniques based on log analysis.

Another crucial factor that previous authors have largely disregarded is the consideration of the time required for VM migration when predicting failures. For successful VM migration, it is imperative to predict the failure before the time it takes to migrate the VM to another physical machine. Unfortunately, most studies have neglected this aspect, leading to sub-optimal migration strategies and potential downtime.

Additionally, if the entire physical server is predicted to fail, all the VMs must be migrated. However, this process can be time-consuming. Therefore, it is crucial to predict the failure of the physical server in advance to ensure sufficient time for the successful migration of all the VMs running on it.

By addressing these research gaps, this study aims to leverage VM and PM logs to accurately predict the failure of any generic VM and the PM. Furthermore, This research will consider the migration time factor to ensure timely and efficient VM migration in the event of failure.

4 Research Questions

1. How to effectively utilize VM and PM logs for machine learning-based VM failure prediction?

2. How to develop a generalized VM failure prediction approach using log analysis, enabling its applicability to a wide range of generic VMs?

3. How can the timing of VM and PM failure prediction be optimized to ensure successful VM migration to a healthy PM, considering the total time required for the VM migration?

5 Aims and Objectives

The main aim of this study is to advance the field of virtual machine failure prediction using log analysis for VM fault tolerance, contributing to improved reliability, and performance of VMs in server environments such as Cloud Data Centers (CDCs).

These are the main objectives of this study:

- To develop a generalized ML-based prediction approach that leverages key events and indicators present in VM and PM logs to predict failures in a variety of VMs.
- To make the prediction time-aware so that it considers the time required for migration to ensure successful VM migration to another physical machine.
- To evaluate the proposed prediction approach and compare its performance against existing techniques using VM and PM log data.

6 Scope

6.1 In Scope

- **VM and PM failure prediction:** The study will focus on developing and evaluating techniques for predicting failures in both VMs and PMs running Ubuntu Server as the host OS, using the logs from the server and the hypervisor.
- **Log analysis:** The research will explore the utilization of logs generated by the server, and QEMU-KVM hypervisor to extract log events, and system states for failure prediction using an ML approach.
- **Online prediction:** The project will emphasize the development of online prediction models that can continuously monitor logs to predict failures on time while considering VM migration time.
- **VM live migration:** The study will consider the use of QEMU-KVM live VM migration.
- **Implementation of a working prototype:** The research will involve the development of a functional prototype that demonstrates the proposed failure prediction techniques using QEMU-KVM as the hypervisor.

6.2 Out of Scope

- **Non-Ubuntu host OSs:** The research will focus exclusively on Ubuntu Server as the host OS running on the physical machines.

- **Hypervisors other than QEMU-KVM:** This study will specifically utilize the QEMU-KVM based hypervisor for the implementation and evaluation of the prototype. Other Cloud Infrastructure software such as OpenStack (OpenStack 2023) will not be considered.
- **Handling unexpected VM failure situations:** This research will focus on predicting failures based on available log data, but pre-failure log data may not exist for some VM failures. That is, the VMs may fail suddenly, without warning and without having any anomalous logs before failure, and in such situations, the system may not be able to predict VM failures.
- **Network-related failures:** The research will not specifically address failures related to network components or network infrastructure. It is important to note that in cases where network failure occurs, migration of the VM may not be feasible or effective, as the migration process itself may be impacted by the network failure.

7 Significance of the Research

This research project aims to enhance existing VM failure prediction approaches by incorporating host server, and hypervisor logs. This contributes to the field by expanding the knowledge and understanding of effective failure prediction strategies in VMs. By accurately predicting VM and PM failures, this research project enables proactive measures to be taken, reducing system downtime and ensuring continuous availability of services. This is particularly significant for critical applications and services that rely on cloud computing infrastructure, such as healthcare systems, financial services, and emergency response systems, and this will help to provide improved user experience and service quality for end-users.

8 Research Approach and Methodology

8.1 Research Approach

- **Data Collection:** Since there are no real-world Linux VM failure log data available, the log data needs to be collected using a testbed, and the VM/PM failures must be simulated using fault injection methodologies because it is infeasible to wait for an actual failure to occur.

- **Testbed Setup:** The set-up testbed contains two physical servers, each equipped with 12-core Intel Xenon processor with 16 GB of RAM. The two servers are interconnected with Gigabit Ethernet. The host OS is Ubuntu Server, and the chosen hypervisor is QEMU-KVM, running variety of VMs. Figure 2 presents the high-level architecture of the testbed that will be used for log data collection.

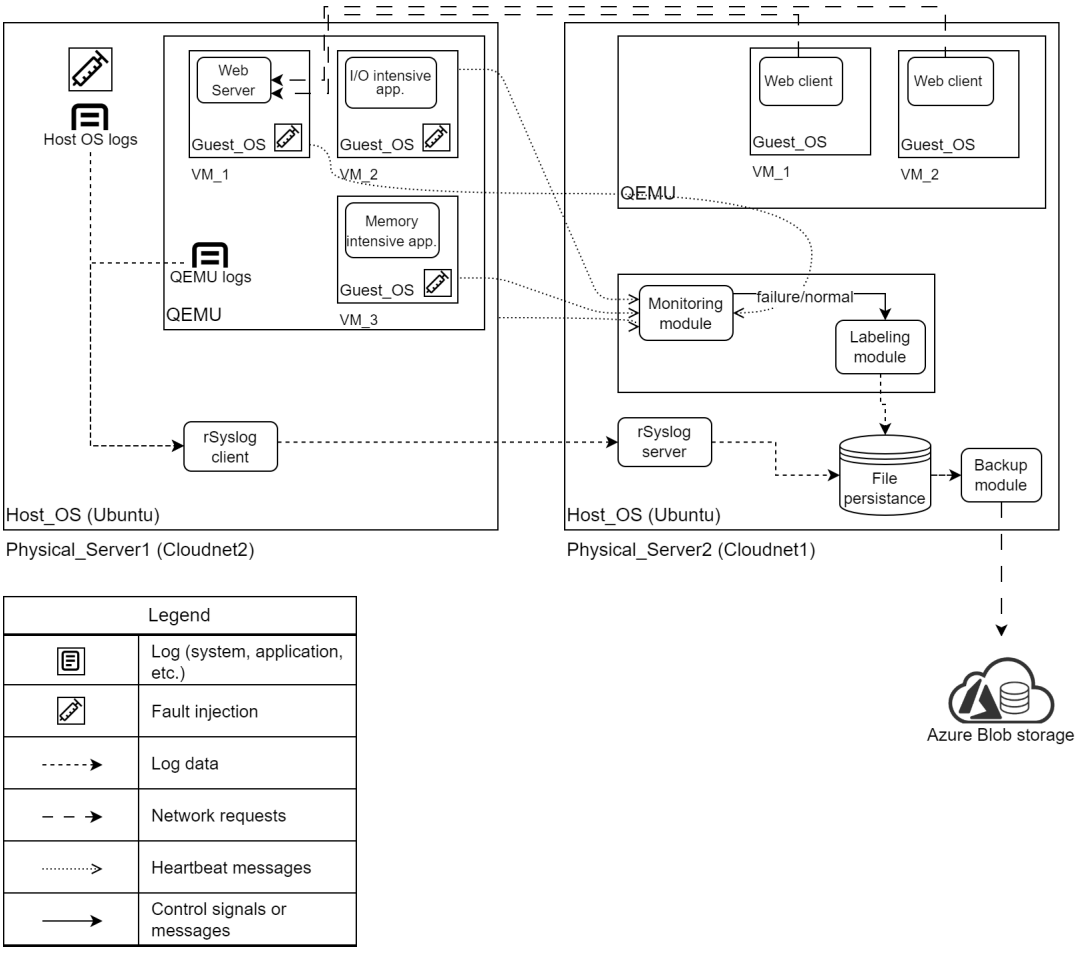


Figure 2: High-level architecture of the testbed

- **Data Preprocessing:** The collected log corpus should be preprocessed in order to use them in ML models. The raw log data are of different formats, so they should also be converted to a uniform format by extracting the timestamp and the log message from the different types of logs. After extracting the log message, the preprocessing step involves the removal of unnecessary logs and converting them to a log key-value representation.

- **ML Model Development:** There are several ML models used for failure predictions in the past, such as random forest, Bayesian models, and SVMs; however, recent studies on the subject used deep learning models such as LSTM and CNN.

  We focused on online anomaly detection models, namely, Numenta (S. Ahmad et al. 2017), KNNCAD (Burnaev and Ishimtsev 2016), ARTtime (Hampton 2021), and EXPoSE (Schneider, Ertel, and Ramos 2016) which proved to be effective for time series anomaly detection. The main idea of our approach is to find anomalous data in the log dataset, which may indicate a possible future VM failure. Further details of our methodology are presented in a later section.

  We aim to explore deep learning based log anomaly detection models such as the LSTM model based on Deeplogs' (Du, F. Li, et al. 2017) "log key anomaly detection model".

- **Timing and Migration Analysis:** The timing aspect of the prediction in relation to VM migration should also be thoroughly analyzed to check for timely prediction of failures. VM migration times can be estimated by performing several VM migrations on the testbed and finding a proper statistical model (mentioned in the "Virtual Machine Live Migration Time Estimation" section above) to calculate the time required to migrate the VM.

- **Prototype Implementation:** A working prototype will be implemented to integrate the developed VM failure prediction technique with QEMU live migration, in order to demonstrate proactive fault tolerance for VMs. Figure 3 presents the high-level architecture of the final implemented system.

8.2 Research Methodology

This research project will follow the Design science research (DSR) methodology to design and evaluate the VM failure prediction system using log analysis. DSR is a research paradigm that try to solve real-world problems by developing and evaluating artifacts. These artifacts can be new technologies, systems, processes or methods. In this context the artifact is the VM failure prediction system. DSR is a cyclic process that involves the following steps:

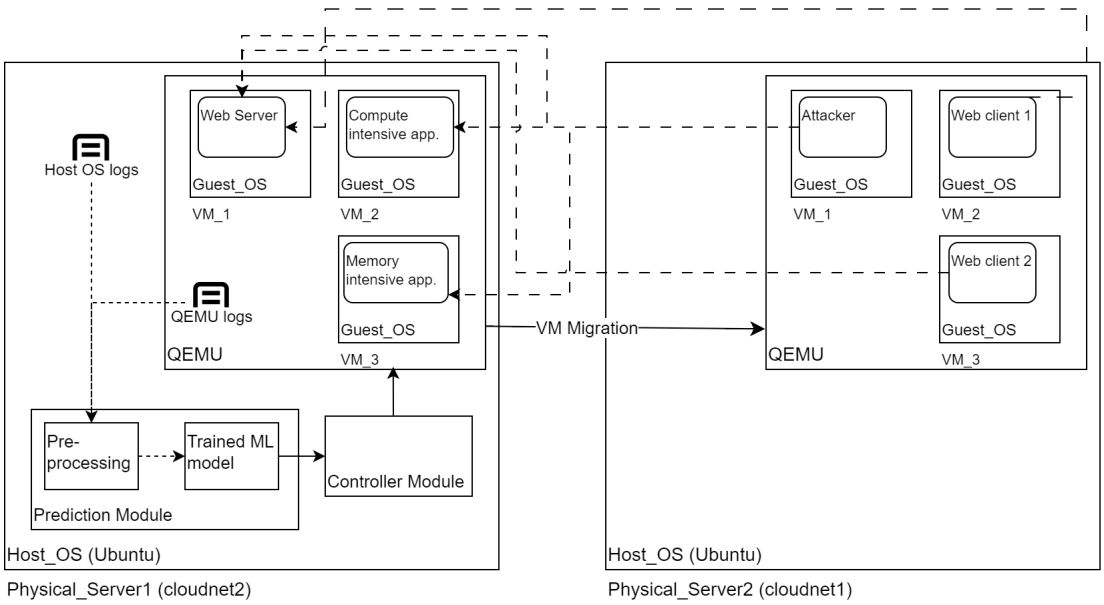


Figure 3: High-level architecture of the full system

1. **Problem identification:** The first step is to identify a real-world problem that needs to be solved. This problem should be significant, and it should be something that can be addressed with DSR.
2. **Design the artifact:** Once the problem has been identified, the next step is to design an artifact that can be used to solve the problem.
3. **Evaluate the artifact:** Once we designed design the artifact, it must be evaluated to see if it effectively solves the problem. This evaluation can be done in a variety of ways, such as through user testing, simulations, or case studies.
4. **Communicate the results:** Once we properly evaluate the artifact, the results of the study need to be communicated to the community. This can be done through publications, presentations, and other means.

There are several advantages of using the DSR methodology for this research project:

- DSR is a well-established approach for developing and evaluating innovative solutions to real-world problems.
- DSR encourages proper evaluation, essential for ensuring that the developed VM failure prediction system is effective.
- DSR encourages the communication of research results to the community, which helps to ensure that the research has a positively impacts the field.

9 Evaluation Plan

9.1 Evaluation of ML models

The developed models and the baseline models can be evaluated using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. Furthermore, true anomaly detection (True Positives) can be identified/categorized by the following methods,

1. ML model detects an anomaly anywhere in the anomalous time series.
2. ML model detects the anomaly in the pre-defined anomalous region in the labelled time series.
3. ML model identifies the anomaly within the anomalous area in the dataset before the VM failure.

Similarly, false anomaly detection (False Positives) can be identified by the following methods,

1. ML model detects an anomaly anywhere in a non-anomalous/benign dataset.
2. ML model detects the anomaly outside the pre-defined anomalous region in a labelled dataset that contains an anomaly.

Also, if the ML model identifies the anomaly in the data set before the failure, time to accurate prediction of failure can be considered as an evaluation metric.

9.2 Whole system evaluation

The implemented prototype system can be evaluated through experiments conducted on the testbed to assess the efficiency and reliability in simulated failure scenarios. The accuracy of prediction, the accuracy of VM migration time estimation and, the number of successful failure predictions and VM migrations over the total number of experiments (accuracy of the full system) will be evaluated.

10 Preliminary Results and Discussion

We have collected nine datasets for OOM failure scenarios so far on the cloudnet2 server, and each dataset contains the following log files,

- Kernel log
- Application logs (CRON, networkd, accountsd, dbus-deamon, snap, etc.)
- Systemd logs
- QEMU logs for each VM

We have also implemented the monitoring module to monitor the VMs and the host continuously to detect VM and host failures. The monitoring module uses a heartbeat protocol where each VM and the host (cloudnet2) send a request to the monitoring module every 30 seconds. The monitoring module is implemented in the second host (cloudnet1), where the streamed log data and the results of the ping requests get collected. If a VM or a host fails to send a request to the monitoring module within 1.5 minutes, it is considered a failure, and the timestamp and the failed VM details are saved to a file.

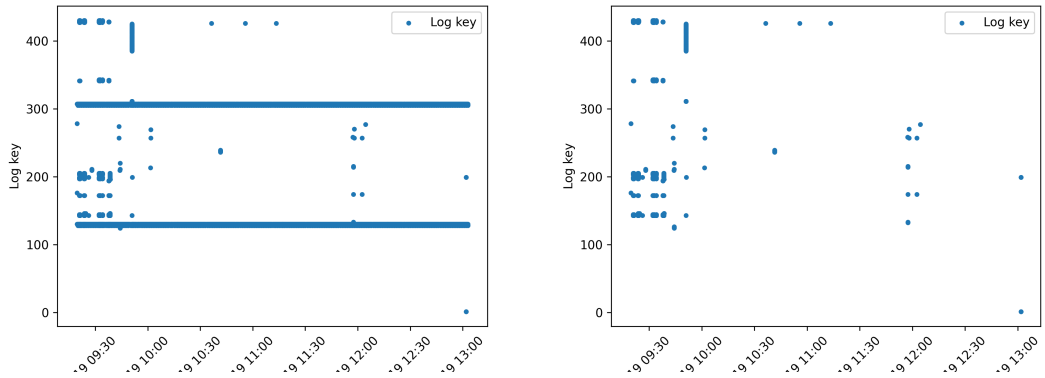
For the pre-processing stage, we go through all the log files in a dataset and split each log line to separate the timestamp and other metadata from the log message. The log message is then passed through the log parser to get the log template key. Then, we output a file with the timestamp and the log key for each log line in the dataset. Finally, we have used the timestamp of the monitoring module results (failure timestamps) to create the final dataset for ML model training and testing.

We have tested SPELL (Du and F. Li 2016) and DRAIN (He et al. 2017) log parsers and chose DRAIN as the suitable log parser because it is state-of-the-art, and we were able to find an open-source implementation of DRAIN by IBM Research, Drain3 (Ohana 2020).

After analysing the logs, we found that most of the log lines are related to CRON logs, which will contribute very little to the VM failure prediction task. So, before proceeding further, we removed all the CRON-related logs from the dataset; as a result, we were able to reduce the size of the log dataset by nearly five times. Figure 4 presents the overview of a pre-processed dataset before and after removing the CRON logs. For this specific dataset, we reduced log lines from 2417 to 487, a 4.9X reduction.

The overall idea of our approach is to find anomalous data in the log dataset. Suppose there are failure indicators in the dataset. In that case, the dataset should deviate from the normal operational condition data, which indicates an anomaly, which in turn suggests a possible fault in the system, which may lead to VM failures. Anomaly detection ML models are only trained on normal state "benign" data. One added advantage of this approach is that most models can be trained on very little data, and they work extremely well in identifying anomalies in the dataset.

To get baseline results, we used several NAB (Numenta Anomaly Benchmark) (S. Ahmad et al. 2017) detectors on the pre-processed dataset. NAB detectors

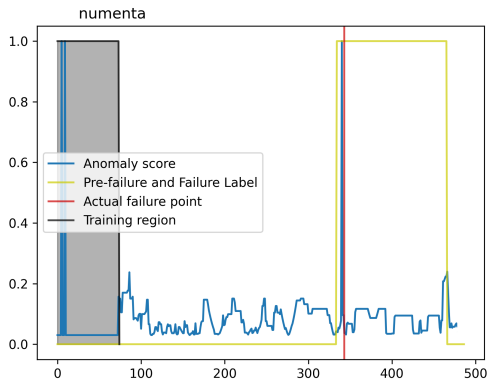


(a) Before removing CRON logs (b) After removing CRON logs

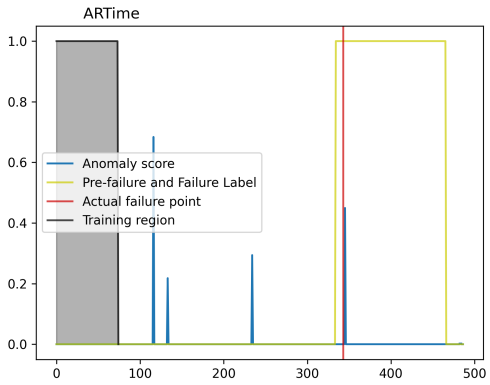
Figure 4: Pre-processed dataset

are state-of-the-art anomaly detection models, and they run unsupervised/semi-supervised and assume the first 15% of the dataset is of normal state data without any anomaly. The models are trained on the first 15% of the dataset and predict anomalies for the rest. We were able to run nine detectors out of fourteen available detectors. Out of the nine detectors, Numenta (S. Ahmad et al. 2017), KNNCAD (Burnaev and Ishimtsev 2016), and ARTtime (Hampton 2021) detectors performed well over the others. The results from EXPoSE (Schneider, Ertel, and Ramos 2016) model are also included for comparison.

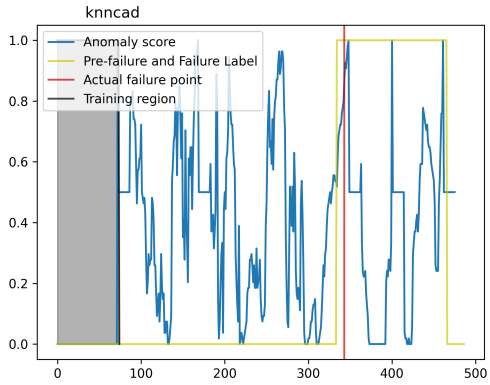
Figure 5 presents the raw results from running the NAB models on a single dataset with a simulated Out-of-memory scenario. With the evaluation criteria mentioned above, we can see that all the models identified that the dataset is anomalous; however, the EXPoSE model marked most of the non-anomalous (normal state) regions as abnormal, suggesting that the EXPoSE model does not perform well in this scenario. With proper thresholds, we can see that the other models detected anomalies within the labelled anomalous region, and the Numenta model detected the anomaly within the region before the VM failure (7 minutes before failure). Also, the Numenta model has no false positives in this dataset (we do not consider the predictions in the training region).



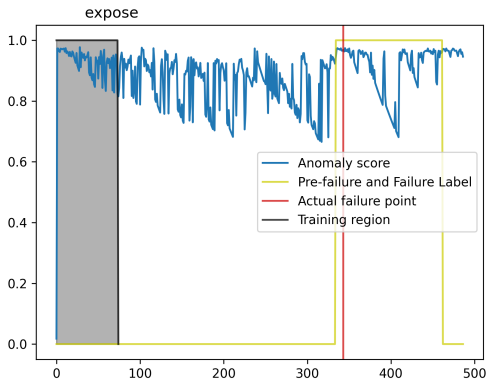
(a) Numenta



(b) ARTime



(c) KNNCAD



(d) EXPoSE

Figure 5: ML model raw results

11 Project Timeline

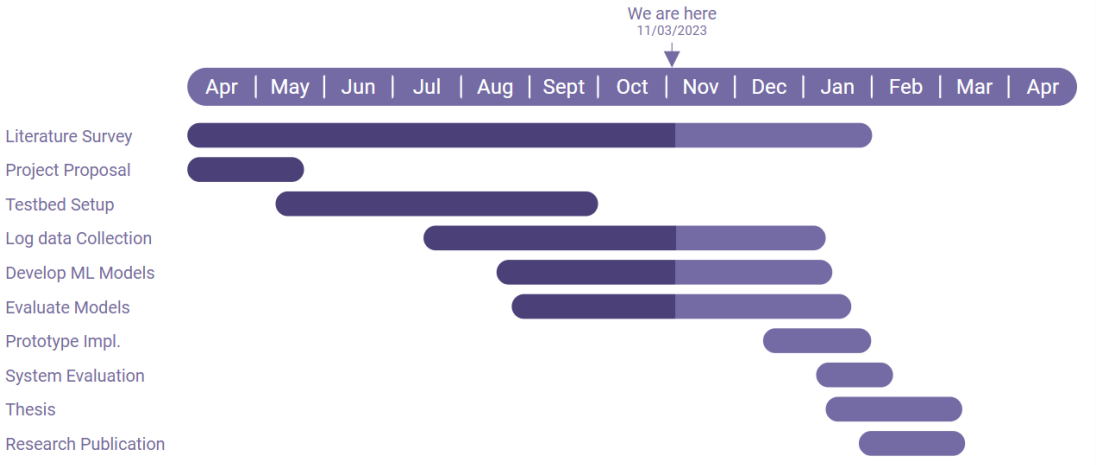


Figure 6: Project timeline

12 Improvements from Feedback

The primary feedback from the evaluation panel was that the simulation of VM failures where the guest OS itself fails is not needed for this research because the software failures inside the VM will not be solved by migration and should be handled by the respective VM user. Migrating a crashed VM does not solve the issue with the VM. As a result, we decided not to collect VM logs from the host OS and the applications running inside the VM. This positively impacted the research because now we are not restricted to Linux-based VMs (guest OS). The failure prediction system is now guest OS invariant and any guest OS that QEMU supports will now be able to use the developed failure prediction system.

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