





provided by a cloud through its own virtualized resources, which are formed over its underlying physical resources. In most cases, a virtualized resource in the cloud is referred to as a Virtual Machine (VM), which is a collection of files that contain specifications and configurations (Devi and Valli, 2021).

It is possible to obtain a significant number of the advantages that are connected with the cloud model as a consequence of the multiplexing. Studies have shown that servers in many existing data centers are frequently underutilized because they are overprovisioned for peak loads. This is the case because of the fact that they are overloaded with resources. An additional result of the frequent changes in workload demand is the placement of Virtual Machines on Physical Machines in an inefficient way, as well as an uneven distribution of resources within the data center (Mishra& Manjula, 2020). This is a consequence that affects both the physical machines and the virtual machines. The underutilization of physical machines is responsible for the waste of resources and the excessive consumption of electricity, whereas the overutilization of physical machines is responsible for the degradation of performance as well as a decline in the quality of service (Ghetas, 2021). This study addresses an issue that is completely different from the one that has been investigated in the past: what are the most effective methods for a cloud service provider to multiplex its virtual resources onto physical hardware in an efficient manner while incurring the least amount of overhead. The following section focused on the previous literatures that are associated with this topic.



## LITERATURE REVIEW

A list of previous literatures that are relevant to this research is included in table 1.

Table 1: Related works

AUTHORS AND YEARS	METHODOLOGY	RESULTS AND FINDINGS
Reddy & Reddy (2023)	The framework uses Universal Unique Identification (UUID) -Blake, Manhattan Distance – Partition Around Algorithm (MD-PAM), Linear Scaling – Crow Search Optimization (LS-CSO), and Anova-Recurrent Neural Network to schedule workflows dynamically in this article. This framework was implemented in three phases.	The results showed that LS-SCO outperformed Crow Search Optimization (CSO), Particle Swarm Optimization (PSO), and Round Robin (RR).
Kruekaew&Kimpan (2022)	The multi-objective optimization-scheduling model using the ABC algorithm and Q-learning (MOABCQ) method, a reinforcement learning technique that speeds up the Artificial Bee Colony Algorithm (ABC) algorithm, is a multi-objective task scheduling optimization based on the ABC algorithm that is proposed as an independent task scheduling approach in cloud computing.	According to the testing results, the MOABCQ approach algorithms performed better than the other algorithms in terms of makespan reduction, cost reduction, imbalance reduction, throughput increase, and average resource usage.
Konjaang& Xu, (2021)	In order to simultaneously lower execution costs and execution makespan, this study expanded on the earlier work "Cost Optimised Heuristic Algorithm (COHA)" and introduced a novel workflow scheduling technique called Multi-Objective Workflow Optimization Strategy (MOWOS).	When compared to the state-of-the-art work, the suggested algorithm's performance increases greatly in large and extra-large workflow jobs compared to small and medium workflow tasks. It can enable all activities to be completed before the deadline and significantly cut costs by 8%, makespan by 10%, and resource consumption by 53%.
Ismayilov &Topcuoglu (2020)	This paper proposed the neural network based non-dominated sorting genetic algorithm (NN-DNSGA-II) algorithm, a prediction-based dynamic multi-objective evolutionary algorithm that combines the non-dominated sorting genetic algorithm (NSGA-II) method with an artificial neural network.	According to metrics used for dynamic multi-objective optimization problem (DMOP)s with unknown true Pareto-optimal front, such as the number of non-dominated solutions, Schott's spacing, and Hypervolume indicator, the NN-DNSGA-II algorithm significantly outperforms the other alternatives in the majority of cases, according to an empirical study based on real-world applications from the Pegasus workflow management system.



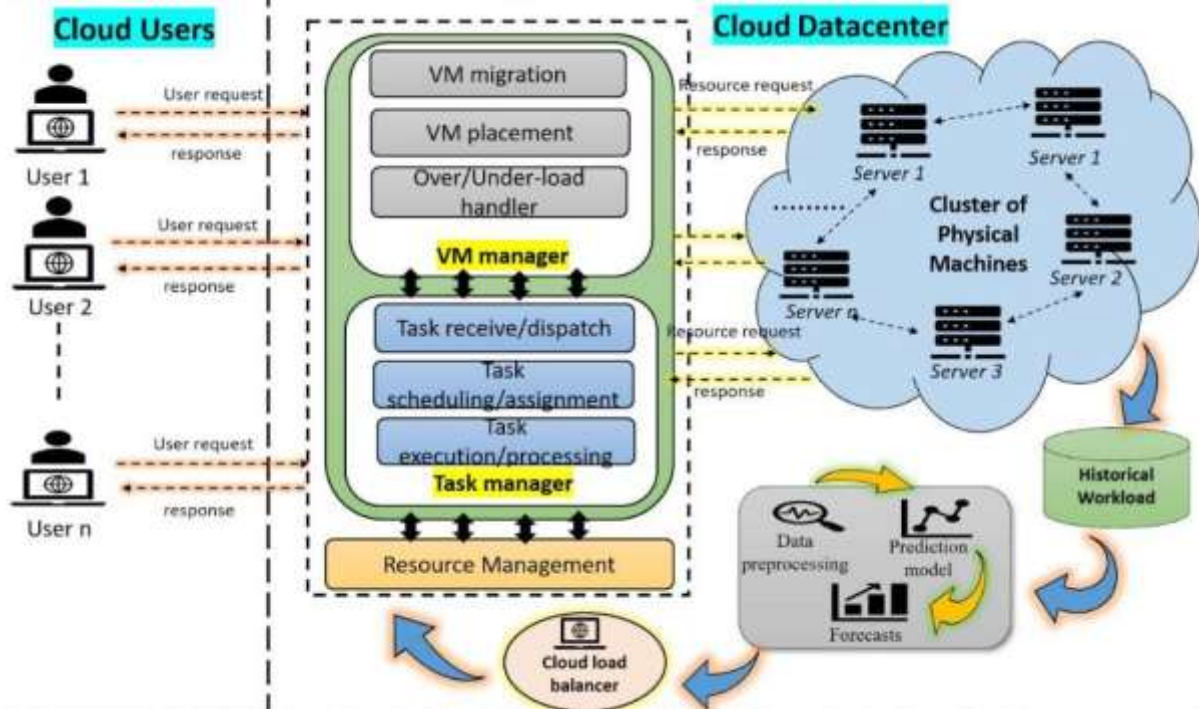


Figure 1: Proposed Multi-Objective Framework for Workload Prediction (Ali, 2022).

In comparison to the solutions that are currently available, the framework that has been proposed is superior since it is able to manage many objectives simultaneously and makes greater use of past data. Furthermore, it is meant to be scalable, which enables it to be utilized in scenarios that include massive cloud infrastructures.

## RESULTS AND DISCUSSIONS

Users need a lot of data because the system allocates resources in an automated manner. But unless users use AWS or Google's data at enormous data centers, it is impossible to obtain a prepared and clean data set for accomplishing such a thing on a modest scale. For this investigation, it has made use of the GitHub data collection. This module is in charge of handling warehouse management, storing raw data, processing it, building machine learning models from the data collected, and distributing the finished models to edges. It is capable of controlling the system.

In the field of machine learning, a number of different classifier algorithms were chosen based on a cross-validation technique. This technique demonstrated that Decision Trees and other relevant models were able to classify data with an accuracy of 83%, which is a sufficient degree of accuracy for the purpose of resource allocation. The data were also evaluated using other methods, such as logistic regression, which had an accuracy of approximately 69%. Additional techniques were also utilized. Because of this, the Decision Tree (DT) classifier has been chosen as the model that maximizes efficiency the most. In order to demonstrate that it will be superior for cloud workload prediction, the following figure provides a graphical depiction of the examination and comparison of several different machine learning techniques.

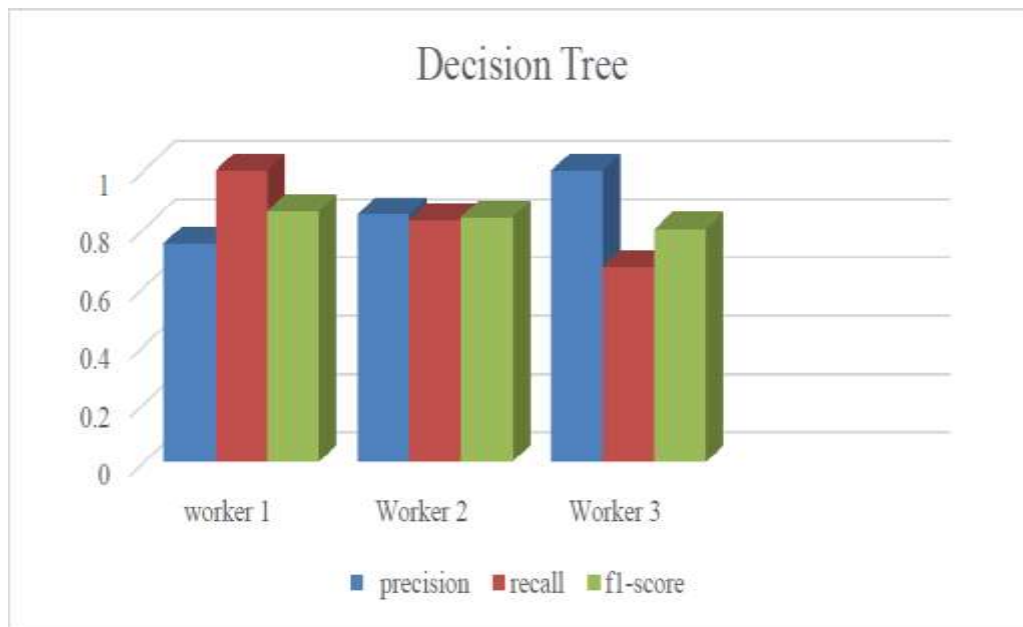


Figure 2: Machine Learning Models Comparison – Decision Tree (DT)



Figure 3: Machine Learning Models Comparison – Logistic Regression (LR)

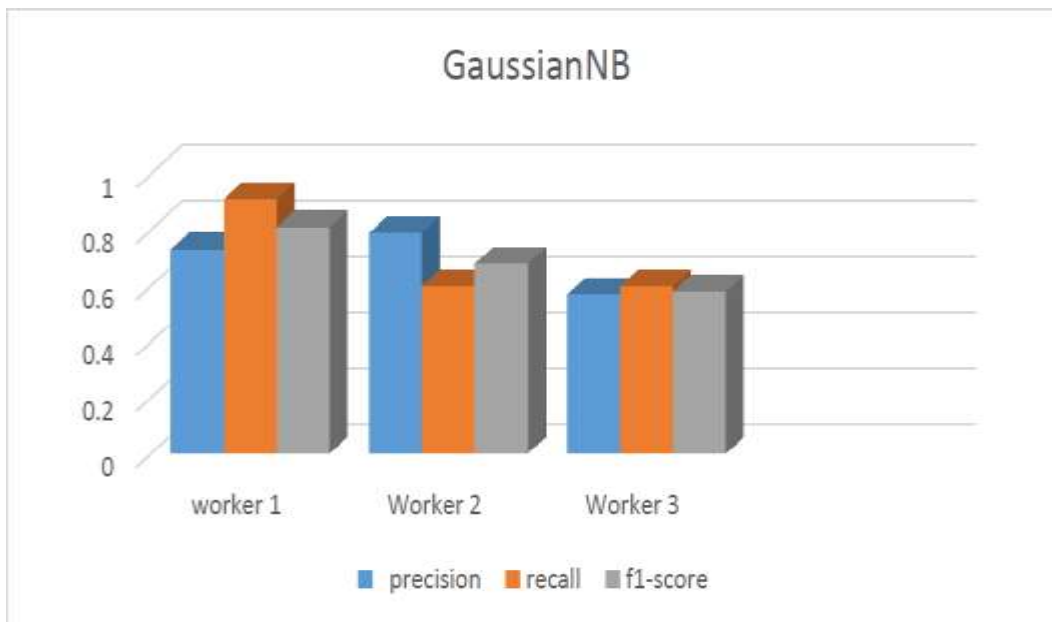


Figure 4: Machine Learning Models Comparison – Gaussian Model Naive Bayes (Gaussian Model NB)







