Optical Interconnection Networks Using machine learning models

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I. Abstract

Optical interconnection networks play a pivotal role in modern computing systems, facilitating high-speed data transmission and communication between various components. With the ever-increasing complexity and scale of these networks, there arises a need for efficient optimization techniques to ensure their optimal results. And leverage machine learning techniques for analyze to optimize optical interconnection networks. Our research focuses on predicting the temporal distribution of optical interconnection networks, a critical factor influencing their overall performance. We experimented with several models techniques and optimizing their hyperparameters to achieve the best performance. Evaluation of the models was based on accuracy score and F1 score, providing insights into their predictive capabilities. Our findings highlight the efficacy of machine learning techniques in analyzing and optimizing optical interconnection networks, paving the way for enhanced performance and efficiency in future computing systems. The findings of the study highlight the capability of utilizing some model techniques to drive progress for optical networking technologies.

After training the model with different model techniques. Each model is evaluated by accuracy score, confusion matrix and f1 score. On the basis of these factors we evaluated the model and identified that which model is giving the best accuracy.

Key Word: Logistic regression, F1 Score, Standard scalar, Hyperparameter tuning, Grid search cross validate, k-fold.

II. Introduction

In the realm of modern computing systems, the efficiency and scalability of data transmission and communication with high speed and low latency. The main goal is to meet the ever-increasing demands for high-speed, low-latency communication among various components within these systems. These networks leverage optical signals to transmit data, offering advantages such as high bandwidth, low power consumption, and reduced signal degradation over long distances.

In this model is trained by some model techniques for analyzing and optimizing optical interconnection networks. To facilitate this investigation, we utilize a dataset sourced from the UCI Machine Learning Repository, containing 640 instances and 10 features relevant to the performance of these networks. The dataset encompasses a wide range of parameters, including node number, thread number, spatial and temporal distributions, as well as various performance metrics such as processor utilization and network response time.

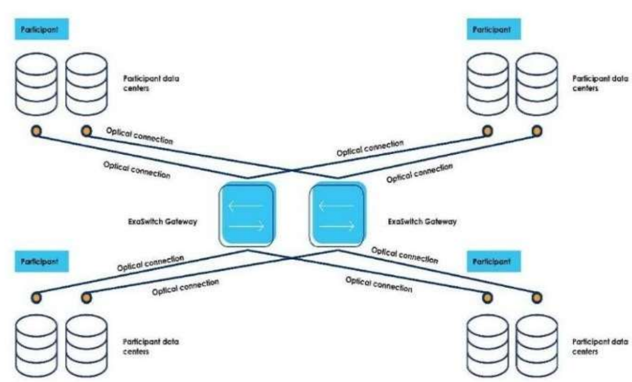

Figure 1: Optical Interconnection Networks

The main moto is to find the target variable that is temporal distribution of optical interconnection networks, a critical factor influencing their overall performance and efficiency. By leveraging machine learning models trained on historical data, we seek to gain insights into the complex relationships between network parameters and temporal behavior, enabling better decision-making and optimization strategies.

By leveraging the capabilities techniques, actively contribute to the ongoing initiatives aimed at optimizing and analyzing optical interconnection networks.

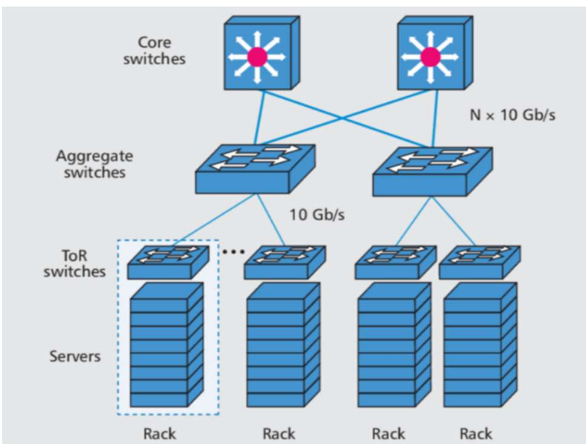

Figure 2: Interconnection Networks architecture

III. Literature Review

In recent years, optical interconnection networks have garnered considerable interest owing to their ability to tackle the escalating need for high-speed and energy-efficient communication in contemporary computing systems. The literature surrounding this subject spans a diverse array of studies, delving into various facets of optical interconnection networks and exploring the utilization of machine learning techniques for their optimization and analysis.

Qixiang Cheng and Madeleine Glick. et al(2019) worked upon Optical interconnection networks play a crucial role in high-performance systems, such as supercomputers and warehouse-scale data centers. These systems have become ubiquitous in modern life, with applications ranging from different fields like entertainment and fashion [1].

Christoforos Kachris, Konstantinos Kanonakis. et al(2013) worked upon this discusses this research focus on some key features of the optical interconnection networks in different aspects. Regarding optical interconnects.

Overall, the literature highlights the growing interest in leveraging machine learning techniques for optimizing and analyzing optical interconnection networks. These approaches offer opportunities for enhancing network performance, reliability, and scalability in modern computing systems.

The key aspect of this to find the best suitable model for the optical interconnection networks in order to transmit the data between two or more components in high speed with low latency. And also it plays a crucial role in model computing systems. And speed of the communication between two components will increase by using the optimal approach.

Table 1: Literature review

Authors	Topic	Year
Qixiang Cheng, Madeleine Glick . Et al	Optical interconnection networks are vital components in high-performance systems, enabling efficient communication and data transfer at high speeds.	2019
Christoforos Kachris, Konstantinos Kanonakis. Et al	focuses on exploring the latest developments and forthcoming obstacles in integrating optical interconnection networks within data centers.	2013

IV. Proposed Methodology

we delineate the methodologies. employed in our research study to analyze and optimize optical interconnection networks using machine learning techniques. and some Data preprocessing steps Standard Scaler(which is used to standardize the data), Label Encoder(to convert categorical data to numerical data). And Confusion matrix like Accuracy Score and F1 score. And hyperparameter tuning.

1. Dataset: It is of text dataset and the dataset used in this project is Optical Interconnection networks taken from the UCI machine learning repositories and it consist of 640 instances and 10 features and it has no null values and the dataset is from 2018. With some attributes.

2. Dataset Preprocessing: preprocessing the dataset obtained from the UCI Machine Learning Repository. This includes handling categorical data and standardizing features to ensure compatibility with machine learning algorithms. We utilize label encoding to transform categorical variables such as "Spatial Distribution" and "Temporal Distribution" into numerical representations. Subsequently, we apply the standard scaler to standardize the features, for handling outliers and the data which is having different units.

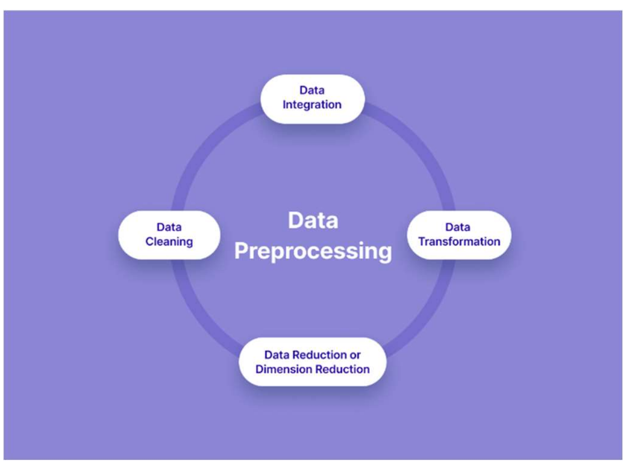

Figure 3: Data preprocessing

3. Train-Test-Split: To train the data, firstly split the data for training and testing into 80:20 that is 80 is for training purpose and 20 is testing purpose. And took temporal distribution as the target variable and remaining as the feature in order train this model for the accurate results. which constitutes 80% of the data, is utilized to train the models, while the remaining 20% is kept aside for evaluating how well the models perform on unseen data. This partitioning ensures that model will able to predict the target variable that is temporal distribution by using the remaining features

4. Machine Learning Models: We experiment with a variety of machine learning models to predict the temporal distribution of optical interconnection networks and all these model techniques comes under classification.

Models used:

i. Logistic Regression.

ii.Random Forest

iii. Support Vector Machine (SVM)

iv. K-Nearest Neighbors (KNN

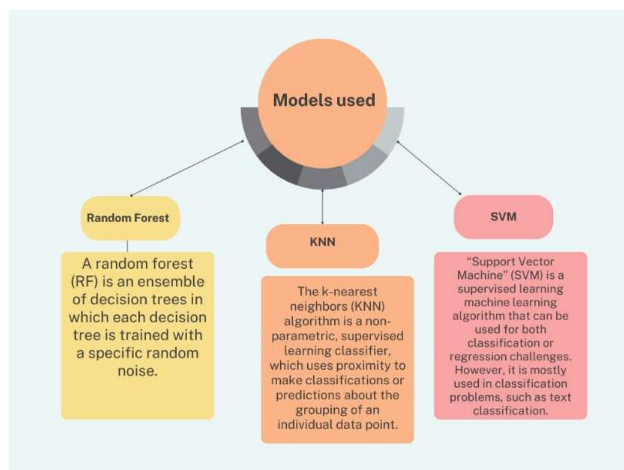

Figure 4: Models Used

5. Hyperparameter Tuning: For training the model ,perform hyperparameter tuning using methods like grid search or random search. Hyperparameters, which dictate the behavior of the learning algorithm and are not learned from the data, are systematically explored across a range of values. This process helps identify the optimal configuration for each model, thereby maximizing its predictive accuracy on the validation set.

6.Evaluation Metrics: We assess the performance of our machine learning models using two primary metrics: accuracy score and F1 score. The accuracy score able to evaluate the model, offering a broad evaluation of model effectiveness. F1 score considers the harmonic mean precision and recall of the model's predictions, is particularly useful in imbalanced datasets where the class distribution is skewed. In this project four different models were used in order to predict the accuracy score and f1 scores. Below are the accuracy score for each model.

Accuracy Scores

- Logistic Regression- 0.705078
- Random Forest - 0.90625
- SVM - 0.9453125
- KNN - 0.8359375

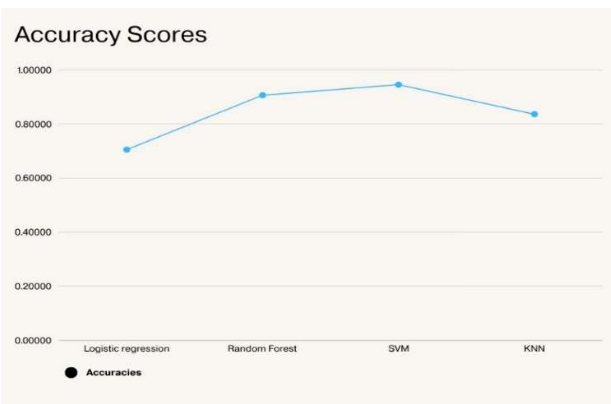

Figure 5: Accuracy Scores

After comparing the accuracy score among all of these four model techniques Support vector machine(SVM) gives the best accuracy score i.e 94%. And support vector machine(SVM) is the best suitable model.

F1 Scores: It means the harmonic mean of the recall and precision.

- Random Forest - 0.9060661
- SVM - 0.9452957851946941
- KNN - 0.8359675572519084

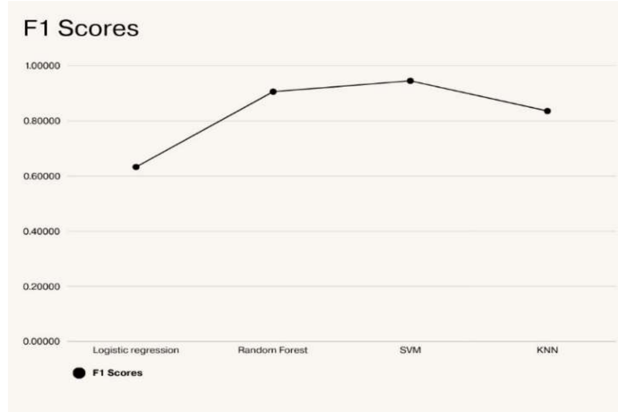

Figure 6: F1 Scores

7.Comparative Analysis: Finally, We perform a comparative analysis of the machine learning models' performance by evaluating their accuracy scores and F1 scores. This analysis allows us to assess how well each model performs in terms of both overall prediction accuracy and the balance between precision and recall. This analysis enables us to identify the most effective model for predicting the temporal distribution of optical interconnection networks and provides insights into the strengths and limitations of each approach.

8.Formulas:

$$\text{Accuracy Score} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

$$\text{F1 Score} = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}}$$

$$\text{Standardized value} = \frac{\text{value - mean}}{\text{Standard deviation}}$$

9.Results: After successfully training the model with four different machine learning techniques, it is evident that SVM stands out as the top-performing model for optimizing the performance of optical interconnection networks. Support vector machine gives an accuracy with 94.53% and an f1 score with 94.53%, SVM demonstrates its capability to effectively capture the intricate patterns and relationships within the dataset. This high level of accuracy and F1 score underscores SVM's suitability for making precise predictions regarding the temporal distribution of optical interconnection networks.

The success of SVM in optimizing optical interconnection networks highlights the importance of selecting the appropriate machine learning technique for the task at hand.

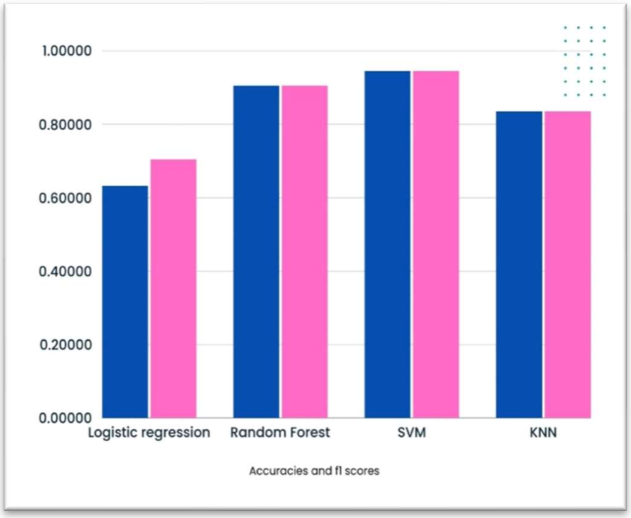

Figure 7: Accuracy and f1 score Comparison

After successfully trained the model with four different techniques in this three model were used by using the hyperparameter tuning with some parameters, and plot the bar graph by comparing the model accuracies and f1 score. In that SVC gives the best accuracy score as well as the highest f1 score so we considered the svc is best suited for this dataset to trained the model.

Table 2: Accuracy and f1 score

Models	Accuracy Scores	F1 scores
Logistic Regression	0.705078125	0.63281
Random Forest	0.90625	0.906066176
SVM	0.9453125	0.945295785
KNN	0.8359375	0.835967557

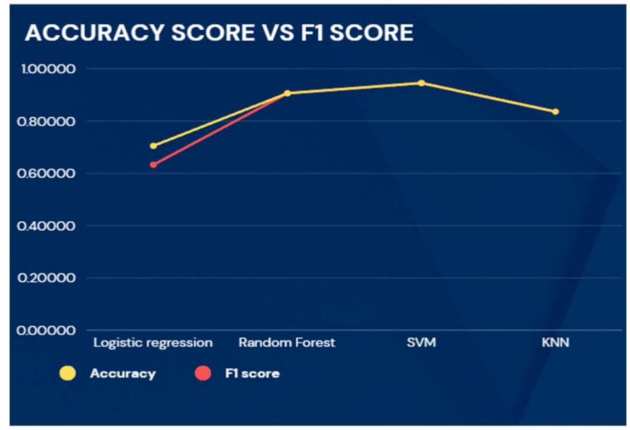

Figure 7: Accuracy score vs f1 score

V. Future Scope

Although our current research study offers analyzing and optimizing optical interconnection networks, several avenues for future exploration and development in this field remain open.

1. Advanced Feature Engineering: Future research endeavors can concentrate on exploring more sophisticated feature engineering techniques to capture additional nuances and complexities within optical interconnection networks. This may involve the extraction of higher-order statistical features, time-series analysis, or the incorporation of domain- specific knowledge to enrich the feature space and improve model performance.

2. Enhanced Learning models: Enhanced learning models offer substantial potential for advancing the state-of-the-art in analyzing optical interconnection networks. These architectures excel at learning intricate patterns and dependencies within data, potentially enabling more accurate predictions and insights into network behavior.

3. Real-Time Monitoring and Adaptation: Future research can focus on the development of real-time monitoring and adaptation mechanisms for optical interconnection networks using machine learning. By leveraging streaming data and online learning techniques, it may be possible to continuously monitor network performance, detect anomalies, and dynamically adapt network configurations to optimize performance and resource utilization in real-time.

VI. Conclusion

we explored some of the machine learning models for analyzing and optimizing optical interconnection networks. Leveraging a dataset sourced from the UCI Machine Learning Repository, we conducted a comprehensive study to predict the temporal distribution of these networks, a crucial factor influencing their overall performance and efficiency. Through our experimentation with some learning model techniques we gained valuable insights into their predictive capabilities in the context of optical interconnection networks. Our findings underscore the efficacy of machine learning techniques in capturing the predictions regarding network behavior. Among the models evaluated, SVM emerged as the most promising, achieving an impressive accuracy of 94% and confusion matrix and an F1 score of 94%. This highlights the potential of SVM as a powerful tool for optimizing and analyzing optical interconnection networks. Additionally, random forest, logistic regression, and KNN also demonstrated competitive performance, providing valuable alternatives for different use cases and scenarios.

Our research contributes to the ongoing efforts in advancing the understanding and optimization of optical interconnection networks in modern computing systems. we have demonstrated the potential to enhance network performance, reliability, and efficiency, ultimately contributing to the advancement of computing technology.

In conclusion, our study underscores the importance of integrating machine learning techniques into the analysis and optimization of optical interconnection networks. By continuing to explore these avenues of research and innovation, we can unlock new insights and capabilities that drive the evolution of computing systems towards greater performance and efficiency.

VII. References

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