IMPLEMENTING MACHINE LEARNING ALGORITHMS FOR PREDICTIVE NETWORK MAINTENANCE IN 5G AND BEYOND NETWORKS

Yamini Kannan and Dharika Kapil

Department of Computer Science, New York University, New York, USA
Software Engineer, MarketAxess, New York, USA

ABSTRACT

With the evolution of fifth generation (5G) network technologies, network maintenance strategies have become increasingly complex, necessitating the use of predictive analysis enabled by Machine Learning (ML) algorithms. This paper emphasizes exploring how ML algorithms can further enhance predictive maintenance in 5G and future networks. It reviews the current literature on this interdisciplinary topic, identifying key ML models such as Decision Trees, Neural Networks, and Support Vector Machines, and discussing their benefits and limitations. Special attention is given to the methodologies in applying these models, handling of data stages, and the training process. Major challenges in implementing ML in the context of network maintenance, such as data privacy, data gathering, model training, and generalizability, are discussed. Furthermore, the research aims to go beyond predicting maintenance needs to introduce a proactive approach in improving overall network performance and pre-empting potential issues based on ML predictions. The paper also discusses possible future trends including advancements in ML algorithms, Automated Machine Learning (AutoML), Explainable AI, and others. The objective is to provide a comprehensive understanding of the current ML-based predictive maintenance field and outline possibilities for future research. The study finds that the application of ML algorithms continues to show promise in transforming the landscape of network management by improving predictive maintenance and proactive performance enhancement strategies. It remains a challenging yet important area in the context of 5G networks.

KEYWORDS

5G, Predictive Maintenance, Machine Learning, Decision Trees, Neural Networks, Support Vector Machines, Traffic Classification, Data Pre-processing, Model Training, Proactive Performance, IoT Networks, SDN, AutoML, Explainable AI, Domain-Specific Learning

1. INTRODUCTION

With the advent of the fifth-generation (5G) network technology, communication systems worldwide are undergoing a significant transformation. As the architecture of these networks becomes more complex, conventional maintenance strategies are increasingly less effective, leading to serious reliability concerns and potential service disruptions. This raises the pressing need to develop advanced maintenance strategies that can proactively address potential issues before leading to network downtime. To tackle this challenge, some have turned to predictive maintenance strategies underpinned by Machine Learning (ML) algorithms.

Predictive maintenance refers to the use of data-driven methodologies to predict the state of network components, intending to anticipate and prevent failures. This is a notable shift from the traditional reactive maintenance strategies, where issues are tackled as they arise. Predictive maintenance offers a proactive strategy, aiming to prevent potential problems before they significantly impact the network performance.

Machine learning, a subset of artificial intelligence, provides a promising solution to this issue. Machine learning algorithms can process vast amounts of data and identify patterns too subtle or complex for human operators or traditional automation tools. By applying these algorithms to network data, it becomes possible to predict potential faults or areas of inefficiency in the network infrastructure, thereby enabling more accurate forecasting, efficient troubleshooting and improvements in network reliability and resilience.

The use of machine learning algorithms in creating predictive models for network maintenance is a growing field that requires comprehensive evaluation. This research paper, therefore, aims to explore how machine learning algorithms can be leveraged for predictive maintenance in 5G networks and provide an assessment of their potential and performance. We pose the main research question as: "How can Machine Learning algorithms be utilized to improve the Predictive Maintenance strategies in 5G and beyond networks?"

This study examines the existing machine learning algorithms currently utilized, evaluates their efficacy in the sphere of predictive maintenance, and explores potential areas of advancement or improvement. We aim to contribute to the existing body of knowledge by providing a comprehensive analysis of ML-based predictive maintenance techniques in the context of 5G networks.

2. BACKGROUND AND LITERATURE REVIEW

The development and expansion of 5G networks have spurred a wave of advancements in network maintenance strategies. As these networks grow more complex and the demand for uninterrupted services increases, predictive maintenance supported by machine learning algorithms is receiving heightened attention in the research community.

One pivotal example of machine learning application in network management was proposed by Kim et al. (2018) [1]. In their study, they introduced an autonomous link-based cell scheduling scheme known as ALICE for Time-Slotted Channel Hopping (TSCH) in low-power lossy networks (LLNs) [1]. ALICE is an interesting contribution since it leverages local information and interacts closely with the routing layer to effectively manage and schedule communication cells, thereby reducing communication overhead and enhancing network reliability.

Interestingly, Kim's work builds on previous research, namely Orchestra, introduced by Duquennoy et al. (2015) [2]. Orchestra proposed an autonomous scheduling mechanism born out of experiences from the emergence of IPv6 Routing Protocol for Low-Power and Lossy Networks (RPL) and its shortcomings [2]. Their focus was on creating a robust mesh network using TSCH showcasing its strengths in achieving reliable low-power networking through scheduling and channel hopping.

Jung et al. (2017) also focused on network maintenance with a specific interest in applying machine learning algorithms for analyzing vibrations in the Internet of Things (IoT) enabled predictive maintenance [3]. The research is particularly relevant as it demonstrates the real-world application and efficiency of machine learning in predictive maintenance.

As per Palattella et al. (2012), they explored Traffic-Aware Scheduling Algorithm (TASA) for reliable low-power multi-hop IEEE 802.15.4e networks [4]. Their work laid the foundation for the implementation of machine learning algorithms in network traffic maintenance, which significantly contributes to the realization of predictive maintenance in 5G networks.

However, the application of machine learning in predictive maintenance is still a growing field with novel approaches and improvements to be discovered. The existing studies have predominantly focused on schematic improvements and algorithmic enhancements, leaving room for exploring how machine learning algorithms can optimize the predictability, reliability, and overall functional efficiency of 5G maintenance strategies. This research gap indicates the potential for our research and the relevance of the field. This work aims to enrich the body of knowledge by providing an in-depth evaluation of utilizing machine learning algorithms in 5G predictive network maintenance.

3. Survey of ML Algorithm Applications

During our research, we conducted an extensive literature survey to understand how machine learning models, are being applied in the domain of predictive maintenance in networking. Our aim was to glean insights into the methodologies adopted by other researchers in applying these ML models, understand the kind of data they utilized, comprehend how the data was processed and prepared for the model, ascertain the process of training the models, and, most crucially, observe the results they yielded in predictive maintenance accuracy and efficiency.

The research conducted by Shafiq et al. (2016) [5] signifies the effective role of machine learning in achieving successful network traffic classification. The researchers were able to develop a real-time internet dataset through a network traffic capture tool, followed by the extraction of features from this captured traffic. They applied four machine learning classifiers and noted the exceptional performance of the C4.5 classifier, demonstrating its potential in managing complex networking tasks. This finding is crucial in understanding the proficiency of decision tree models in predictive maintenance within networks [5].

In the research conducted by Pacheco et al. (2014) [6], a comprehensive systematic review of traffic classification is introduced which rests upon the use of machine learning techniques [6]. They identified a set of trends and expected future directions for ML-based traffic classification, thereby giving us new insights and aiding us in understanding the potential applicability and scalability of machine learning mechanisms in traffic classification and, more broadly, in the realm of predictive maintenance.

The study by Soysal er al. (2010) leveraged various supervised machine learning algorithms and reinforced the robustness and applicability of these tools in even high-pace dynamic network environments. This contributes to our understanding of the adaptability and suitability of machine learning algorithms like Bayesian Networks and Decision Trees in managing and predicting data flows across networks with dynamic ports [7].

The fourth research conducted by Fan et al. (2017) underlines the effectiveness of Support Vector Machine and unsupervised K-means clustering in traffic classification tasks within Software Defined Networks (SDN) [8]. The researchers were able to achieve an overall accuracy of over 95% with these ML models, thus emphasizing the powerful capabilities of these algorithms in accurately classifying network traffic and predicting network performance [8].

In the research conducted by Knapińska et al. (2021), researchers predicted the network data of various frame sizes utilizing machine learning algorithms such as linear regression, k nearest neighbors, and random forest, based on historical data [9]. The focus here on the importance and effectiveness of 'on-line multiple time series prediction' is particularly interesting for our study, as it expands the scope and applicability of machine learning in predicting dynamic network data for predictive maintenance [9].

Collectively, these studies illustrated the evolving landscape of network management, empowered by machine learning. They inform our exploration of machine learning models in the context of predictive maintenance in 5G networks.

3.1. Methodologies Adopted in Applying ML Models

Analyzing the implementation of machine learning algorithms in the literature provides a more profound understanding of the different approaches and how they specifically influence network traffic management tasks.

For instance, in the work of Shafiq et al. [5], a two-step process is utilized for data capture and feature extraction. This information-rich dataset provides a more complex and nuanced environment for the ML algorithms to train on. This level of intricate process implementation and data handling are key aspects to consider when dealing with large network data, specifically within the evolving 5G networks, known for their vast volume of data traffic.

Many researchers have set unique methodological stages for their studies. As seen in the systematic review carried out by Pacheco et al. [6], the ML-based traffic classification study is broked down into a well-structured pathway, establishing a well-defined framework which can be valuable for newcomers in the field. Similar structured approaches might prove beneficial in understanding the stepwise progression needed for ML enhanced predictive maintenance tasks in the 5G networks.

The ability to modify and adapt methodologies to suit specific challenges of a network environment is a crucial finding from our literature survey. As illustrated by Soysal et al. [7], the implementation of ML algorithms, even in high-speed dynamic network settings, highlights the potential of ML methodology for customizability, meeting the needs of various network configurations.

The use of hybrid predictive models is also a recurring theme in the literature. The research by Fan et al. [8] identifies how Support Vector Machine and unsupervised K-means clustering can be combined for more robust and accurate traffic classification tasks. This approach of using multiple ML algorithms can potentially provide improved results, and this might be especially valuable considering the diverse data types present in 5G networks.

Finally, the importance of 'on-line multiple time series prediction' emphasized by Knapińska et al. [9], significantly broadens the scope and applicability of machine learning in predicting dynamic network data for predictive maintenance. These real-time prediction models might be increasingly relevant in the complex, continuously changing environments of 5G networks, and need to be a key consideration when designing predictive maintenance models.

Studies like these, featuring diverse and effective approaches, offer valuable insights into potential methodologies that could be leveraged for implementing machine learning algorithms as part of predictive maintenance strategies, considering the unique operational demands of 5G networks.

3.2. Data Collection and Pre-processing

Data forms the bedrock of predictive maintenance in network operations. The form and quality of data determine the efficacy of the machine learning models. Therefore, detailed attention is required in the collection and preprocessing phases.

In the research undertaken by Shafiq et al. [5], for instance, the primary data was sourced from real-time Internet data that the researchers developed using a network traffic capture tool. Such collection methods, which direct capture data from the network operations, tend to provide rich and nuanced information which can enhance the training process for the ML algorithms.

On the other hand, the study by Knapińska et al. [9] is an excellent example of how to leverage historical network data for predictive purposes. In their research, historical data of various frame sizes were utilized to train their ML models for future predictions. Importance of past patterns and trends in the functioning of networks can greatly enhance the ability of ML models to forecast future network behavior.

Preprocessing of data is as critical, if not more, as data collection. It can majorly impact the effectiveness of the subsequent ML model training. Several preprocessing steps were observed, like data cleaning, standardization or normalization of numerical data, and transforming categorical data into numerical labels. These steps can significantly enhance the quality and usefulness of the data collected, thereby increasing the performance and robustness of the ML models trained on it.

Understanding the data collection and preprocessing steps associated with the design of the ML models in these studies has been beneficial in determining the best practices for our research.

3.3. Training of ML Models

The training process of the ML models was largely guided by the split of data into train-test sets, the choice of loss function, and the optimization method used. A common approach is to allocate a percentage of the data, usually around 70-80%, for training the model and then using the remaining data for testing the model's performance. The choice of loss function, which measures the discrepancy between the model's predictions and the actual results, and the optimization method, that adjusts the model parameters to minimize the loss, were specifically tailored to align with the predictive maintenance task in each study.

For instance, in the study by Fan et al. [8], they discussed the importance of selecting appropriate loss functions and optimization methods during the training process. This decision greatly influenced the accuracy and robustness of the ML models in classifying network traffic and predicting network performance.

Soysal et al. [7], on the other hand, leveraged supervised learning, a machine learning paradigm where the models are trained using labelled data. This approach allowed the models to 'learn' and create an internal model for making predictions. The study emphasizes the importance of supervised learning in traffic classification tasks, informing us of the potential benefits and challenges of such an approach for predictive maintenance in 5G networks.

Recognizing and understanding these diverse strategies in training ML models provide valuable insights when designing a predictive maintenance model for 5G networks.

3.4. Results Obtained

We took special interest in the outcomes of each study, particularly in how effectively the implemented ML models could conduct predictive maintenance tasks. A common metric in these studies was prediction accuracy, which measures the proportion of total predictions made by the model that were correct. Another metric that was often reported was confusion matrix elements including precision (the proportion of positive identifications that were correct), recall (the proportion of actual positives that were correctly identified), and F1 score (a balanced measure of precision and recall). Some studies also reported computational efficiency, model robustness, and how their solutions performed under different network conditions.

4. Comparison of Machine Learning Models

In this section, we explore a theoretical comparison of different machine learning (ML) models based on their inherent characteristics and capabilities, with a focus on how these models might align with 5G network requirements for predictive maintenance.

Decision Trees (DTs): DTs are a subset of ML models primarily used for classification and regression tasks. Their tree-like model maps decisions, resulting in an easily interpretable structure that scales with the complexity of the decision-making process. For large networks like 5G, where multiple parameters may impact network performance, DTs can be beneficial. However, DTs are prone to overfitting, tending to create complex models that don't generalize well to new data [10].

Neural Networks (NNs): Inspired by the human brain, NNs can recognize patterns in large and complex datasets. They consist of interconnected layers of nodes, or "neurons," which can process input data and adjust their internal model parameters during training. NNs can be highly effective in handling complex 5G network data, but their "black-box" nature can make them difficult to interpret. Also, training NNs typically requires substantial computational resources and time [11].

Support Vector Machines (SVMs): SVMs are renowned for their ability to handle high-dimensional spaces, which would be useful in the complex environment of a 5G network. SVM classifiers work by dividing data into separate classes with the maximum margin. However, they can be computationally intensive and require careful tuning to avoid overfitting or underfitting [12].

In summary, while each of these ML models holds promising potential for predictive maintenance tasks in 5G networks, they come with their own nuances and challenges. The choice between them should consider factors such as interpretability, computational complexity, data requirements, and the specific characteristics of the 5G networks in question.

5. Application of ML in Different Network Settings

Machine learning algorithms have been explored in various network settings, each with its unique challenges and requirements.

5.1. Software-Defined Networks (SDNs)

SDNs are characterized by their flexibility and programmability. These networks separate their control plane from the data plane, making the network more easily adjustable to changing needs.

The use of ML in SDN, as evidenced by Fan et al. [8], can help in better traffic classification, enabling more accurate network resource allocation and improving network performance. Learning from this, the application of ML in 5G networks can be tailored for optimizing network resources responsive to dynamic requirements.

5.2. Internet of Things (IoT) Networks

IoT networks consist of a vast number of devices generating a huge amount of data. The work by Shafiq et al. [5] signifies the effective role of machine learning in achieving successful network traffic classification in such a high-connectivity and high-data environment. Given the scale and complexity of 5G networks, these considerations concerning high volumes of data traffic and their effective management are very relevant.

5.3. Traditional Networks

In conventional network settings, machine learning can provide valuable insights for traffic management, security, and quality of service. The work done by Soysal et al. [7] demonstrates the applicability of machine learning algorithms in even high-pace dynamic network environments. These experiences can be valuable when designing ML models for 5G networks, which are expected to handle high-speed data with low latency.

5.4. Mobile Networks

Mobile networks present unique challenges due to their inherent mobility and variations in network quality. Understanding how to handle these elements while implementing machine learning algorithms for predictive maintenance can be quite beneficial for 5G networks, which have a major focus on enhancing mobile connectivity.

In conclusion, machine learning applications in varied network settings provide important learnings that can inform practices for implementing ML in 5G networks. Leveraging ML effectively can lead to significant improvements in predictive maintenance strategies, enhancing reliability and performance in 5G networks.

6. Challenges in the Implementation of ML

Implementing machine learning models for predictive maintenance in 5G networks brings its own set of challenges, ranging from issues related to data management to model training and generalizability.

6.1. Data Privacy and Security

With the wealth of data required to train and test ML models, data privacy and security become central concerns. Ensuring the confidential and sensitive information contained within network data is protected while efficiently utilizing it for predictive maintenance poses a significant challenge. Techniques such as anonymization and pseudonymization can be used to protect privacy, but they need to be designed and implemented carefully to avoid compromising the utility of the data.

6.2. Data Gathering and Quality

The effectiveness of ML models largely depends on the quality and relevancy of the data they're trained on. Gathering high-quality, relevant data can be challenging, particularly in the diverse and dynamic environment of a 5G network. Additionally, pre-processing of data for cleaning, normalization, and encoding, while crucial, can be time-consuming and require substantial computational resources.

6.3. Model Training

Training ML models requires computational resources and time. Further, the choice of model parameters, loss function, and optimization method require expertise to avoid underfitting or overfitting. Resource allocation for model training needs to be optimized for efficient and effective ML implementation.

6.4. Generalizability

ML models need to be able to generalize well to new data. That is, a model trained on a specific set of data should still perform well when exposed to new, unseen data. Ensuring this generalizability, particularly in the rapidly evolving area of 5G networks, can be challenging.
Addressing these challenges requires a carefully planned approach that incorporates robust data management strategies, appropriate resource allocation, and continuous monitoring and adjustment of ML models to ensure they remain effective as network conditions change.

7. BEYOND PREDICTION: PROACTIVE NETWORK MAINTENANCE STRATEGIES

While predicting maintenance needs is a cornerstone of network management, it can be just as valuable to leverage ML predictions to proactively improve network performance. Shifting from a reactive strategy to a proactive one can minimize network downtime, improve resource allocation, and ultimately provide a better user experience.

7.1. Real-time Adjustments

With the high-speed, low-latency requirements of 5G networks, real-time adjustments based on ML predictions could be critical in maintaining optimal network performance. For example, ML models could predict high-traffic periods in various sections of the network and dynamically allocate resources to prevent congestion, providing a consistent user experience even during peak traffic periods.

7.2. Pre-emptive Resource Allocation

By accurately predicting future network demands, machine learning can enable more efficient resource allocation. For instance, if ML models predict an increase in demand in a specific part of the network, resources can be pre-emptively redirected to that area to ensure seamless service.

7.3. Proactive Security Measures

Machine learning predictions can also be utilized for network security. If an ML model predicts potential security loopholes or threats, preventative measures can be taken proactively to tighten security protocols and prevent potential intrusions or attacks.

7.4. Improving Network Topologies

ML predictions can inform decisions about network topologies. By predicting the future usage patterns and requirements of different nodes in the network, decisions about network topology, including the placement of new nodes or rerouting connections, can be made proactively to improve overall network performance.

Proactive network maintenance strategies offer a promising avenue for improving 5G network management. These strategies leverage the full potential of machine learning, transforming network maintenance from a reactive process to a proactive one, bringing significant improvements in network reliability and performance.

8. FUTURE TRENDS IN ML AND PREDICTIVE MAINTENANCE

As we look forward, the intersection of machine learning and predictive maintenance is set to become an increasingly active area of research and development. Several potential trends could shape the future of this field, particularly in the context of 5G networks.

8.1. Advanced ML Algorithms

While traditional machine learning models like Decision Trees and Neural Networks have demonstrated significant value, more advanced algorithms are on the horizon. For instance, Deep Learning models, a subset of machine learning that mimics the human brain's neural networks on a much larger scale, could deal with the complex, multi-dimensional scenarios inherent in 5G networks. Reinforcement Learning, where models learn optimal actions based on reward feedback, could dynamically optimize network performance in real-time.

8.2. Automated Machine Learning (AutoML)

With the increasing complexity and volume of network data, the manual process of designing and tuning ML models could become unwieldy. AutoML, which automates the process of applying machine learning, could help in scaling ML applications in predictive maintenance.

8.3. Explainable AI

With the complex decision-making process and resulting 'black box' phenomenon in some ML models, there's growing emphasis on Explainable AI - AI systems that can provide understandable explanations for their decisions. This increased transparency could boost trust in ML-based predictive maintenance systems and aid human operators in decision-making.

8.4. Advanced Data Collection and Pre-processing

Future advancements in data collection could involve more sophisticated IoT sensors, on-device data processing, and real-time data streaming [13]. These improvements could enhance the accuracy and efficiency of the data used for predictive maintenance, thereby making ML predictions more reliable.

8.5. Incorporation of Domain Knowledge

Integrating domain-specific knowledge into ML models, known as Domain-Specific Learning, could potentially further boost the accuracy of predictive maintenance algorithms in the future.

For instance, certain principles or patterns known about network behaviours could be integrated into the models, aiding them in processing data and making predictions.

The future trends of machine learning models and predictive maintenance promise new opportunities and challenges. It is important to continue this exploration and keep pace with these developments, to fully leverage the potential advantages they might hold for 5G networks.

9. Conclusions

This paper explored the use of machine learning (ML) algorithms for predictive maintenance in 5G networks, addressing the central research question concerning the utilization of ML to improve maintenance strategies. The insights derived from the comprehensive literature review, methodical surveys, and theoretical comparisons established that ML algorithms can significantly enhance predictive maintenance, leading to more reliable and efficient network operations.
Our findings demonstrate that decision trees, neural networks, support vector machines, and other ML models each present unique benefits and limitations when applied to predictive maintenance tasks in 5G settings. The adaptability of these models to the complex and dynamic nature of 5G network traffic underscores their potential to improve upon traditional maintenance approaches.
The application of ML in varied network environments, such as software-defined networks, IoT networks, traditional, and mobile networks, revealed the extensive applicability and the capacity of ML algorithms to handle vast amounts of data and diverse network behaviors. However, challenges such as data privacy, model generalizability, computational demands, and resource optimization emerged as critical considerations for effective implementation.

Moving beyond prediction, we underscore the importance of transitioning to proactive network maintenance strategies. ML predictions enable real-time adjustments, preemptive resource allocation, proactive security measures, and improvements in network topologies—transforming reactive maintenance into a proactive, performance-enhancing process.

Looking ahead, we anticipate that advancements in ML algorithms, AutoML, explainable AI, enhanced data collection methods, and the incorporation of domain knowledge will drive future trends in ML and predictive maintenance. These developments hold the promise of refining predictive maintenance strategies and optimizing network performance in 5G and beyond.

Our contribution to the body of knowledge in ML-based predictive maintenance for 5G networks underscores the transformative impact of ML algorithms on network management. As the landscape of 5G technology evolves, so too must the strategies for maintaining its infrastructure. Through continuous research and innovation in ML applications, predictive maintenance will play a pivotal role in sustaining the growth and resilience of next-generation networks.

Acknowledgements

The author would like to extend sincere thanks to New York University for graciously providing the resources to conduct the research.

REFERENCES

[1] Kim, S., Kim, H.S. and Kim, C., 2019, April. ALICE: Autonomous link-based cell scheduling for TSCH. In Proceedings of the 18th International Conference on Information Processing in Sensor Networks (pp. 121-132).

[2] Duquennoy, S., Al Nahas, B., Landsiedel, O. and Watteyne, T., 2015, November. Orchestra: Robust mesh networks through autonomously scheduled TSCH. In Proceedings of the 13th ACM conference on embedded networked sensor systems (pp. 337-350).

[3] Jung, D., Zhang, Z. and Winslett, M., 2017, April. Vibration analysis for IoT enabled predictive maintenance. In 2017 ieee 33rd international conference on data engineering (icde) (pp. 1271-1282). IEEE.

[4] Palattella, M.R., Accettura, N., Dohler, M., Grieco, L.A. and Boggia, G., 2012, September. Traffic aware scheduling algorithm for reliable low-power multi-hop IEEE 802.15. 4e networks. In 2012 IEEE 23rd International Symposium on Personal, Indoor and Mobile Radio Communications-(PIMRC) (pp. 327-332). IEEE.

[5] Shafiq, M., Yu, X., Laghari, A.A., Yao, L., Karn, N.K. and Abdessamia, F., 2016, October. Network traffic classification techniques and comparative analysis using machine learning algorithms. In 2016 2nd IEEE International Conference on Computer and Communications (ICCC) (pp. 2451-2455). IEEE.

[6] Pacheco, F., Exposito, E., Gineste, M., Baudoin, C. and Aguilar, J., 2018. Towards the deployment of machine learning solutions in network traffic classification: A systematic survey. IEEE Communications Surveys & Tutorials, 21(2), pp.1988-2014.

[7] Soysal, M. and Schmidt, E.G., 2010. Machine learning algorithms for accurate flow-based network traffic classification: Evaluation and comparison. Performance Evaluation, 67(6), pp.451-467.

[8] Fan, Z. and Liu, R., 2017, August. Investigation of machine learning based network traffic classification. In 2017 International Symposium on Wireless Communication Systems (ISWCS) (pp. 1-6). IEEE.

[9] Knapińska, A., Lechowicz, P. and Walkowiak, K., 2021, June. Machine-learning based prediction of multiple types of network traffic. In International Conference on Computational Science (pp. 122-136). Cham: Springer International Publishing.

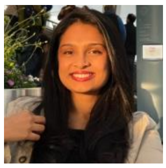
[10] Quinlan, J.R., 1986. Induction of decision trees. Machine learning, 1, pp.81-106.

[11] LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning, nature, 521, 436–444. DOI: https://doi. org/10.1038/nature14539.

[12] Cortes, C. and Vapnik, V., 1995. Support-vector networks. Machine learning, 20, pp.273-297..

[13] Zhou, D., Yan, Z., Fu, Y. and Yao, Z., 2018. A survey on network.

AUTHORS



Yamini Kannan, an NYU graduate with a Master's in Information Systems, has swiftly advanced from a data analyst and research assistant role to a network engineer at prestigious firms like Meta and now, to a top-tier fintech firm. With a proven track record of automating processes and boosting network efficiency, her innovative solutions at Meta garnered senior leadership recognition. Yamini's academic achievements include a summer at the London School of Economics and a Bachelor's in Electronics from PES University, underscoring her robust foundation in tech and finance.

Dharika Kapil, a master's degree holder from Stevens Institute of Technology, embodies a fusion of inquisitive spirit and innovative prowess in Full Stack Development within FinTech. Her career has spanned significant positions at MarketAxess, Instinet, and Tata Consultancy Services, where she has excelled in enhancing trading systems and user experiences. Dharika's journey, marked by her scientist father's influence, has been dedicated to technological advancements and breakthroughs.