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Enhancing QoS with Deep Learning: A Comprehensive Literature Review on Model Optimization and Advanced Data Labeling

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Abstract - This literature review is based on 70 research studies and deals with the issue of optimizing deep learning algorithms and data labeling for network Quality of Service (QoS) classification. It was found that 60% (42 out of 70) of the studies performed showed an inherited optimization need in leveraging deep learning techniques and 67.14% (47 studies) showed the same in data labeling techniques. The intricacy involved in computational processes pertaining to deep learning models poses a significant challenge, as it entails considerable resource investment during the phases of model training and execution. Models can be optimized through hyperparameter tuning, changing network architecture or adding other strategies such as transfer learning which improve reliability and scalability. Also, LSTM networks and other related techniques are effective in capturing temporal phenomena surrounding network traffic, thus enhancing the model's relevance to real-world situations. Equally important is the optimization of data labeling, where challenges such as class imbalance can be resolved through oversampling, undersampling or generating synthetic data. The inclusion of accurate, complete and consistent datasets improves training efficiency. The author's conclusions accentuate that both enhancing the deep learning process and data labeling techniques should be considered for the effective and accurate development of network QoS classification.

Keywords: Deep Learning Optimization, Data Labeling, QoS Classification.

1 Introduction

A literature review for such purposes is intended to assess various strategies that can improve deep learning model performance in classifying network services based on bandwidth, in addition to integrating better data labeling methodologies to improve model accuracy in real-time environments [1]. Deep learning model optimization techniques in network service classification have to address class imbalance in the dataset and try to reduce overfitting in CNN architecture [2]. Some methodologies that deserve investigation include employing data augmentation techniques, optimal feature selection processes, and integrating regularization techniques to overcome overfitting issues. Sophisticated labeling techniques may require employing accurate and consistent real-time data to improve model performance in intrusion detection and network classification tasks [3].

Implementation of these techniques calls for an in-depth knowledge of bandwidth-related factors involved with network services, in addition to an ability to process bigger and heterogeneous datasets

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[4]. With an exploration of deep learning model optimization techniques and integration of advanced labeling techniques, this literature review hopes to provide deep insight and pragmatic solutions to improve performance of models in classifying network services based on bandwidth [5]. This review will also investigate an assortment of optimization techniques that can be applied to deep learning models specifically with respect to classifying network services vis-à-vis bandwidth [6]. One particular approach that will be considered includes using data augmentation techniques, which could be of use in reducing class imbalance in the dataset [7].

Additionally, the review will explore suitable feature selection methodologies and regularization techniques' application to combat overfitting in Convolutional Neural Network models [8]. These methods are expected to improve both model accuracy and generalizability in network service classification [9]. Further, this literature will discuss performing advanced data labeling methodologies using real-time data to make models effective in network classification and intrusion detection tasks [10]. By stressing data accuracy and authenticity, it is argued that application of these advanced labeling methodologies can make a substantial contribution to improving the model's capability to identify network service requirements based on bandwidth issues [11]. One highly established method of reducing class imbalance in datasets lies in employing data augmentation practices [12]. Via data augmentation, new forms of previously available data examples can be presented to enable the model to learn from a myriad of possible real-life scenarios [13]. Efficient feature selection is a critical building block to overall model performance improvement [14]. Within the specific domain of classifying network services based on bandwidth, identification of informative features relevant to the task at hand will enable the model to make more accurate predictions [15]. Overfitting is a common shortcoming in deep learning practices, especially for Convolutional Neural Network models [16]. Use of regularization methodologies like dropout or L1/L2 regularization can aid in eliminating overfitting issues and enhancing model capabilities of generalization [17]. Use of advanced labeling methodologies in conjunction with sophisticated data labeling techniques must involve use of accurate real-time data relevant to prevailing network scenarios [9]. Thus, it allows the model to make better judgments regarding network service requirements [18].

Parallel with network service categorization, advanced data labeling practices can improve model efficacy in terms of intrusion detection [19]. Coupled with integration of genuine, real-time information, the model can demonstrate increased sensitivity in detecting newer security threats [20]. Ongoing developments and improvements in such practices are expected to play an important role in optimizing model performance in network service classification based on bandwidth, simultaneously enabling improved intrusion detection with improved performance [21]. Within deep learning practices applicable to computational networks, issues concerning class imbalance in datasets and overfitting in models are commonplace issues faced by practitioners from the domain of data labeling classification [2]. Intentional countermeasures are therefore necessitated in dealing with these two issues, ensuring that optimal model performance in network service classification based on bandwidth is achieved [22]. Along with practices geared at data augmentation, it was found helpful for such purpose in this work to apply undersampling and oversampling approaches to counter class imbalance [23]. By reducing instances that are affiliated with the majority class (undersampling) or increasing instances that are affiliated with the minority class (oversampling), an improved dataset is achieved for training the model [24]. Additionally, in addressing issues of overfitting in architecture of Convolutional Neural Networks, aside from regularization with dropout or L1/L2 regularization, transfer learning based on pre-trained models may offer an efficient solution [25].

By using insights from modern models, this method enables better learning with reduced chances of overfitting [25]. It is vital to examine the use of advanced techniques of labeling with respect to their performance and efficiency in dealing with real-time applied data [26]. Use of advanced algorithms for handling real-time data offers promise for accelerating the labeling process and ensuring the accuracy of applied data [27]. Depending on their ongoing progress, it is expected that these methods shall play an important role in further improving model performance, especially for efficient classification of network services based on bandwidth [28].

2 Materials and methods

This research methodology is a literature review summary of the 70 studies on network classification using deep learning. The main goal of this methodology is to provide a guideline for the deep learning optimization and data labeling strategies to help classification of network services by bandwidth. We searched for writings with intent across a variety of databases that were relevant to this literature review. The ensuing files incorporated specific keywords such as "deep learning," "network classification," "data labeling" and "bandwidth." Filters were set up to make sure only high quality studies made it through, with an emphasis on articles published in respected journals or conferences peer reviewed with an impact so significant they should be considered authoritative [29]. In order to make the review process systematic and clearer, the study uses the PRISMA framework. This allows for a thorough study and analysis of research, with key points being algorithms, results as well as current areas that need more attention. The papers selected first by PRISMA must meet certain predefined criteria. These include how solid they are as research (given publication year, sample size and geographical scope). This systematic approach means that we can thoroughly review what the effectiveness of deep learning models in network classification is. Nevertheless, optimization of model performance in classifying network services according to bandwidth still needs greater attention at several key points. First, ways to handle class imbalance like undersampling and oversampling are very effective strategies. By reducing the number of samples from the majority class (undersampling) or increasing the number of samples from the minority class (oversampling), a balance in the dataset can be created which the model requires [30]. Besides from that, another possible choice is to use transfer learning techniques from models that have been successful [15]. The implementation of state of the art data labeling techniques not only requires these important aspects of quality but also emphasizes speed and efficiency in handling real time accurate data [31],[32]. With the concepts and procedures of modern algorithms in real time data operations, the speed for data labeling can be accelerated so higher rates are assured [33][34]. By taking an overall and comprehensive approach to all of these strategies, it is hoped that model performance in classifying network services by bandwidth will be significantly improved. All methods used must be written in this section. The method should be written using several sub headings such as time and place of research, materials and equipment, research and experiment design, and any other relevant information.

2.1 Machine Learning Methods Used and How They WorK

In this research we classify and analyse the machine learning methods adopted in each of the reviewed studies, assessing their role and purpose with respect to the specific problem of network classification. It provides details on those algorithms that were applied along with the configurations and settings made to obtain the best result possible. Moreover, it requires a thorough comprehension of how each machine learning method operates. It includes the training, prediction, and assessment of the performance of the models involved using applicable metrics [35]. This research also undertakes a detailed examination of prior study findings. This study consists of analyzing how effective machine learning techniques have been in solving class imbalance problems in data sets as well as employing Convolutional Neural Network models [23] to overcome overfitting problem.

Additionally, the research discusses the impact of data augmentation techniques, relevant feature selection, and regularization for improved performance of the model. By analyzing the results of previous studies and reviewing the literature, this research suggests further advances in the combination of undersampling and oversampling methods to handle class imbalance in datasets [36]. For future development, implementation of transfer learning approaches based on successful models, and the design of advanced data labeling strategies focused on speed and effectiveness in handling streaming data should also be considered. This research seeks to bridge gaps in the literature and enhance performance of models in identifying services based on bandwidth and intrusion detection through a more contemporary and granular approach [37] by incorporating these recommendations.

2.2 Deep Learning Methods Used and How They Work

For this review, we concentrate on the application of deep learning methods, describing the approaches and neural network architectures adopted including, but not limited to, CNN, the types of the network architectures such RNN or LSTM, and their incorporation into research to identify network classification [38]. Deep learning approaches to network classification are fascinating, but complex. This research will carry on if more is known about the machine learning methods employed and how they function. Moreover, milling meditative study discuss previous knowledge findings can lead to be a foot in house befriend along with give useful involvement aeons old machine scrutiny methods in conquering class unsympathetic inwardly datasets respectively extract trick rank hour out Convergence quarters arisen esthetic neural work in extirpate model. This study can be bolstered by including contributions of data augmentation methods, feature selection that are relevant to relevant features, and where feature sets are vast regularization. In addition, they should place a stronger emphasis on what deep learning methods were used, CNN, RNN, or LSTM because it is crucial to give insight into the exact way that they can be applied to network classification [39]. Given these factors, this research can play a major role in developing accurate and faster bandwidth based network service classification models. Combining these recommendations, this work promises to provide a more comprehensive and profound insight on methods capable of enhancing model performance to be used on network service classification [11].

2.3 Advantages of This Research

This paper may be the first to compare methods using tools developed for deep technical comparisons traditional approaches such as statistical testing or existing technology evaluations typically document a distinct advantage of the approach taken, be it in accuracy, computational efficiency, or generalization. Where appropriate, percentage figures and specific numbers are presented to show the exact improvements and successes achieved. Advancing this research takes a more in depth look at the machine learning algorithms you are using and what happens under the hood. It is expected to enhance the understanding of how each method can actually affect model performance in bandwidth-based network service classification [21]. Moreover, a more in depth exploration of the results of past studies may help gather useful information regarding the effectiveness of the machine learning techniques for finding solutions to dataset class imbalance and to deal with the overfitting problem in Convolutional Neural Network (CNN) models [40].

2.4 Weaknesses of This Research

The limitations or the shortcomings of the methods employed are also provided, which suffer from overfitting, large training data, or perform poorly in some conditions. Where applicable, percentage values and specific information graphically laying out the shortfalls are included to provide context on further areas for development. Analysis of Machine Learning Methods and Deep Learning Used [41] To further this research, a more in-depth analysis of the machine learning techniques and their functioning is necessary. This would provide a deeper insight of how each of the methods can change the performance of a model in network service classification driven by bandwidth [28]. Also, by allowing for a more in-depth, detailed analysis of prior experimental results can provide valuable insight into the success of machine learning methods addressing class imbalance in datasets as well as overfitting problems in Convolutional Neural Network models [42]. In the context of network classification, a deeper look into the specifics of which types of deep learning techniques were implemented, such as CNN, RNN, or LSTM, will provide a deeper perspective. In the light of all this, this work is expected to provide data-driven insights for designing more effective and efficient models for classification of network services based on bandwidth [43]. Moreover, undersampling and oversampling methods to overcome class imbalance in datasets should be combined and related future developments taken into more account [44]. Transfer learning from established models, and better strategies for labeling data while balancing between speed and efficiency due to handling near real-time data will also be aspects that better be developed in the future. Consolidating these suggestions promise a more integrated and thorough understanding of methods applicable to network service classification system to enhance model performance end to end to translate this research into practice.

2.5 Unresolved Issues and Areas for Improvement

We outline the features of network classification which existing methods do not yet effectively resolve. These concerns are either challenges not yet met by existing science or proposals to enhance a technique or suggest a new approach for future studies [45]. Lastly, this study has its share of limitations and necessary progress is still required in this field of research. For instance, greater insight into how parameter changes impact deep learning model performance and outputs. Thus it is required to perform a sensitivity analysis of key parameters (like learning rate, number of layers, dropout rate, etc.) to gain an understanding of their impact on model performance in this context [46]. In future work, the importance of using the suitable algorithms for model optimization process can also be taken into consideration. In addition, managing class imbalance in datasets is still an open problem. This approach must be followed carefully and in detail to implement undersampling and oversampling techniques to avoid losing important data which leads to a successful operation on this matter [22]. Considering more complex network problems and conditions would also allow us to gain further practical implications of the classification models developed. It is expected that this research can provide an invaluable contribution to the future generation of accurate and efficient network service models (especially when performing more profound research through comprehensible and systematic analysis and exploration). This study assesses the literature review of 70 journals regarding deep learning to examine the gaps in specific areas, including the optimization of deep learning and data labeling. The review test table to study prior art works on deep learning to investigate the requirement for optimization of deep learning and need to label data. Table 1 below shows a table we have created.

Table 1. Sampling of Three Studies Conducted for Detailed Review Testing

Title	1. Machine Learning Method used and how it works	2. The Deep Learning Method used	3. The advantages of this research	4. Weaknesses of this research	5. Which has not been completed from this study
Method for Multi -Task Learning Fusion Network Traffic Classification to Address Small Sample Labels [47]	Multi-Task Learning (MTL) How MTL works: Combining several related tasks into one learning model. Sharing parameters between tasks, so that the transfer of information occurs across different tasks. Prevent overfitting on one particular task by forcing models to study relationship"&"s between tasks.	Convolutional Neural Networks (CNN), Sparse Autoencoders (SAE), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) How Deep Learning works: CNN: Use the conversational layer to extract the spatial features of data. SAE: use the autoencoder layer to study the representation of rare and dense data. Gru: uses a recurring unit layer to process data sequences. LSTM: Using a recurring unit layer with the gate mechanism to study long -term dependence in the order of data.	Reduced dependence on labeled data: The MTEFU algorithm significantly reduces the need for manually labeled data for traffic classification. The paper shows that with only 150 labeled samples, MTEFU can achieve an accuracy of 94%, which is comparable to single-task learning using a fully labeled dataset of 6139 samples. This is a significant advantage as labeling data is often time-consuming and expensive. Improved accuracy: By leveraging information from related tasks (bandwidth and duration prediction), the MTEFU algorithm can achieve higher classification accuracy compared to single-task learning, especially when labeled data is limited. Real-time prediction: The method focuses on analyzing the first few packets of traffic, enabling real-time classification without waiting for the entire flow to complete. This is crucial for online applications where timely decisions are necessary.	Model complexity: The MTEFU algorithm, due to its multi-task nature, requires more parameters and potentially longer training times compared to simpler baseline models. This could be a concern for resource-constrained environments. Performance variation across tasks: While the MTEFU algorithm shows promising results for traffic classification, its performance for predicting duration is slightly lower compared to other tasks and methods. This indicates that further optimization might be needed for specific tasks. Limited dataset: The research primarily focuses on the QUIC dataset. While this dataset is diverse and representative of real-world traffic, further validation on additional datasets is necessary to assess thegeneralizability of the method.	Exploring semi-supervisory learning strategies to further reduce the need for labeled data. Handling the problem of class imbalances in a network traffic classification data collection. Integrate transfer learning mechanisms to speed up the training process and increase accuracy in new tasks.
The Application of Deep Learning for Network Traffic Classification [48]	This research does not use the Machine Learning method	This study uses several Deep Learning methods: Stacked Autoencoder (SAE): The SAE model consists of several layers of the Autoencoder model, where the output of the first layer of Autoencoder is used as an input for the next autoencoder layer. The last layer is classification. Convolutional Neural Network (CNN): 1D-CNN: Processing traffic data as a byte circuit, converting it into a grayscale image matrix. 2D-CNN: Change traffic data into 2-dimensional grayscale images. 3D-CNN: Change traffic data into 3-"&"dimensional data by adding time	High accuracy: Deep learning models, particularly 3D-CNN and LSTM, achieve high accuracy in classifying network traffic. The paper cites examples with F1 scores reaching 96.4% and 96.1% respectively. Automatic feature extraction: Deep learning models can automatically learn features from the data, eliminating the need for manual feature engineering, which is time-consuming and requires domain expertise. End-to-end learning: Deep learning models can learn the entire mapping from raw input data to output classification, simplifying the process and potentially improving performance.	Computational complexity: Deep learning models, especially LSTM and 3D-CNN, require significant computational resources for training and inference. This can be a challenge for resource-constrained environments. Data requirements: Deep learning models typically require large amounts of labeled data for training, which might not be readily available for all types of network traffic. Interpretability: Deep learning models are often considered black boxes, making it difficult to understand how they arrive at their classifications. This can be a concern in applications where explainability is important.	Exploring semi-supervised and unsupervised methods for traffic classifications that require a little or without labeling. Consider the new and developing deep learning algorithm to increase classification accuracy. Shows the practical application of the m"&"ethod discussed in real world settings. Comparing the performance of the method discussed with traditional methods of network traffic classification

Title	1. Machine Learning Method used and how it works	2. The Deep Learning Method used	3. The advantages of this research	4. Weaknesses of this research	5. Which has not been completed from this study
		dimensions to 2D image. Long Short-Term Memory (LSTM): Repeated nerve networks that can study the temporal aspects of traffic data.			
Machine Learning and Deep Learning [49]	Regression: Statistical methods used to predict continuous value (continuous) based on input variables.	Convolutional Neural Network (CNN): Neural network architecture specifically designed to process image - based data.	Explore the use of the Machine Learning and Deep Learning method to predict product demand. Using a large and diverse data collection to train models. Achieve high prediction accuracy. Provides valuable business insight about the factors that affect product demand.	Potential overfitting, because a model that is too complex can learn from noise in data. Dependence on data quality, so incomplete or noisy data can affect the performance of the model. High computing requirements, especially for complex deep learning models.	Increasing prediction accuracy: Research can explore other techniques to increase prediction accuracy, such as using a model ensemble or regularisation. Factor Analysis of Influence: Research can analyze further the factors that influence product demand to provide deeper insights. Applications to other domains: The methodology developed in this study can be applied to other domains that require demand predictions. Real time evaluation: Research can develop a system to evaluate the performance of the model in real-time and make adjustments if needed
	Ways of working: Build a model that maps the input variable to the target output value. The model is trained using a labeled data collection, where the target output value is known. After being trained, the model can be used to predict new output values "&"for data that are not visible before.	Using a conversation filter to extract the features of the image. Apply the activation function to limit the range of output values. Pooling to reduce the dimensions of features. Repeating these steps through several layers to extract high levels. Use a layer that is completely connected to make predictions.			

3 Results and discussion

In Table 2 through 30, a comprehensive study was conducted to determine the need for optimization, encompassing two segments: deep learning optimization and data labeling optimization. Each study is accompanied by details as shown in Table 2.

Table 2. Analysis Review of Studies Numbered 1 to 30 Regarding the Need for Optimization

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
1	2024	Method for Multi-Task Learning Fusion Network Traffic Classification to Address Small Sample Labels	Yes	Yes	Needs optimization for multi-task learning and labeling strategies
2	2023	The Application of Deep Learning for Network Traffic Classification	Yes	Yes	High computational complexity and large data requirements
3	2021	Machine Learning and Deep Learning	Yes	Yes	Potential overfitting and dependence on data quality
4	2021	Deep Learning for Network Traffic Classification	Yes	Yes	Requires model optimization and better feature selection

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
5	2022	Importance of Kernel Bandwidth in Quantum Machine Learning	Yes	No	Needs better hyperparameter tuning, no labeling optimization mentioned
6	2021	Network Attack Classification in IoT Using Support Vector Machines	No	Yes	Needs better performance evaluation and feature selection
7	2022	A Qos Classifier Based on Machine Learning for Next-Genration Optical Communication	No	Yes	Needs exploration of additional features and dataset expansion
8	2021	5G/B5G Service Classification Using Supervised Learning	No	Yes	Needs larger dataset and exploration of other factors
9	2022	Towards Qos-based Embedded Machine Learning	Yes	No	Needs expansion to other platforms and better efficiency evaluation
10	2021	Active Learning for Network Traffic Classification: A Technical Study	Yes	Yes	Needs better data labeling methods and model integration
11	2021	Research on Qos Classification of Network Encrypted Traffic Behavior Based on Machine Learning	Yes	Yes	Needs better feature selection and integration with traffic management systems
12	2022	DSOQR: Deep Reinforcement Learning for Online Qos Routing in SDN-Based Networks	Yes	Yes	Needs better prediction interpretation and generalization
13	2022	Deep Reinforcement Learning-Based Network Slicing for Beyond 5G	Yes	Yes	Needs scalability and better generalization
14	2021	A Comparative Study of Traffic Classification Techniques for Smart City Networks	No	Yes	Needs comparison with deep learning algorithms and larger datasets
15	2021	SDN-Enabled Fiwi-IOT Smart Environment Network Traffic Classification Using Supervised ML Models	No	Yes	Needs evaluation with larger datasets and handling encrypted traffic
16	2022	Cellular Network Bandwidth Improvement Using Subscribers' Classification and Wi-Fi Offloading	No	Yes	Needs exploration of other ML algorithms and validation
17	2021	1D-CNN Based Model for Classification and Analysis of Network Attacks	Yes	Yes	Needs hyperparameter optimization and relevant data addition
18	2022	Integrating Compament and Deep Learning on Bandwidth-Limited Image Transmission	Yes	Yes	Needs sophisticated network architecture and optimization methods
19	2023	Machine Learning Based Classification of IoT Traffic	Yes	Yes	Needs data reduction strategies and real-world evaluation
20	2021	A Survey on Machine Learning and Deep Learning Based Quality of Service Aware Protocols for Software Defined Networks	No	Yes	Needs hyperparameter tuning and evaluation on different topologies
21	2021	Traffic Classification for Efficient Load Balancing in Server Cluster Using Deep Learning Technique	Yes	Yes	Needs strategies to overcome data limitations and model integration
22	2022	Machine Learning-Based Qos and Traffic-Awall prediction-assisted dynamic network slicing	Yes	Yes	Needs better resource allocation and prediction accuracy
23	2020	Application Based Online Traffic Classification with Deep Learning Models on Sdn Networks	Yes	Yes	Needs better feature selection and model efficiency
24	2024	A Hybrid Cloud Load Balancing and Host Utilization Prediction Method Using Deep Learning and Optimization Techniques	Yes	Yes	Needs noise handling and better performance analysis
25	2022	Qogmp: Qos -Oriented Global Multi -Path Traffic Scheduling algorithm in defined software network	Yes	Yes	Needs better model integration and delay reduction

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
26	2023	Quality of Service (QOS) Performance Analysis in a Traffic Engineering Model for Next-Geniceration Wireless Sensor Networks	No	Yes	Needs evaluation of more factors affecting service quality
27	2023	Traffic prediction in sdn for Explainable Qos Using Deep Learning approach	Yes	Yes	Needs model testing in real environments and better performance evaluation
28	2021	Optimizing Quality of Service of Clustering Protocols in Large-Scale Wireless Sensor Networks with Mobile Data Collector and Machine Learning	No	Yes	Needs better machine learning methods for large-scale protocols
29	2021	Machine Learning Based Mobile Network Throughput Classification	Yes	Yes	Needs larger datasets and better model structures
30	2024	Evaluation of Machine Learning Algorithm Performance in Malware Attack Predictions	Yes	Yes	Needs better deep learning methods and model evaluation

The summary indicates that out of a sample of 30 research, a considerable number of them, specifically 21 studies (21/30), need to make major improvements in their implementation of deep learning methodology. In addition, a larger number of studies, namely 23 (23/30), require improvements in their data labelling procedures. Approximately 70% of the investigations necessitate optimisation of deep learning, whereas about 76.67% call for enhancements in data labelling. These findings emphasise the urgent requirement for improvements in both domains, indicating that most of the research endeavours are now impeded by subpar deep learning approaches and insufficient data labelling. Therefore, it is essential to tackle these shortcomings in order to enhance the general standard and dependability of the studies. The elevated percentages suggest a prevalent issue that, if remedied, might greatly enhance the effectiveness and accuracy of the research results.

There is an urgent requirement for collaborative endeavours to improve both deep learning technologies and data labelling processes in order to get more reliable and precise research results. Subsequently, a literature review analysis was conducted for studies numbered 31 to 60, totaling 30 studies. The analysis results are presented in Table 3.

Table 3. Analysis Review of Studies Numbered 31 to 60 Regarding the Need for Optimization

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
31	2021	Network Traffic Classification Using Deep Convolutional Recurrent Autoencoder Neural Networks for Spatial-Temporal Features Extraction	Yes	No	To address overlap in classification of network configurations.
32	2020	Network Intrusion Detection System: A Systematic Study of Machine Learning and Deep Learning Approaches	Yes	Yes	High model complexity and class imbalance problems.
33	2024	Securing Mobile Edge Computing Using Hybrid Deep Learning Method	Yes	No	To facilitate effective collaboration between EDGE and Cloud resources.
34	2023	Semi-Supervised Alert Filtering for Network Security	Yes	No	To improve reliability and effectiveness in various network security scenarios.
35	2023	Deep Learning-Based Attack Detection and Classification in Android Devices	Yes	No	Further implementation and evaluation of the new screening method.

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
36	2023	Comparative Study of Network Intrusion Detection Using Machine Learning: (SVM and ANN Method)	Yes	No	Dataset limitations and lack of recent data, false positive rates.
37	2020	Network Intrusion Detection By SVM & ANN With Feature Selection	No	Yes	Lack of quantitative results and outdated dataset.
38	2022	A Comparative Study between Machine Learning and Deep Learning Algorithm for Network Intrusion Detection	Yes	No	Limited dataset and computational resources.
39	2023	A Comparative Study of Machine Learning Algorithms for Intrusion Detection in IoT Networks	Yes	Yes	Limited exploration of Deep Learning and limited dataset diversity.
40	2020	Network intrusion detection system: A systematic study of machine learning and deep learning approaches	Yes	Yes	High computational cost, dataset limitations, class imbalance problem.
41	2020	CDC: Classification Driven Compression for Bandwidth Efficient Edge-Cloud Collaborative Deep Learning	Yes	No	High computational overhead and limited evaluation scenarios.
42	2023	Network traffic classification model based on attention mechanism and spatiotemporal features	Yes	Yes	Data dependency and limited interpretability.
43	2024	Traffic Sign board image Classification by using Deep Learning Techniques	No	Yes	Limited dataset size and lack of real-world testing.
44	2024	Applying Deep Learning Techniques for Network Traffic Classification: A Comparison Study on the NSL-KDD Dataset	Yes	No	Limited dataset and need for more comprehensive comparisons.
45	2024	Multi-Stage Learning Framework Using Convolutional Neural Network and Decision Tree-Based Classification for Detection of DDoS Pandemic Attacks in SDN-Based SCADA Systems	Yes	No	Computational cost and limited dataset size.
46	2024	Evaluating deep learning variants for cyber-attacks detection and multi-class classification in IoT networks	Yes	No	Limited comparison with other methods and computational cost.
47	2024	ITC-net-audio-5: an audio streaming dataset for application identification in network traffic classification	Yes	Yes	Limited application coverage and small sample size.
48	2023	Multi-Classification and Tree-Based Ensemble Network for the Intrusion Detection System in the Internet of Vehicles	Yes	Yes	Limited focus on unknown threats and deployment challenges.
49	2023	An Enhanced Encrypted Traffic Classifier via Combination of Deep Learning and Automata Learning	Yes	No	High computational complexity and limited interpretability.
50	2023	An E2E Network Slicing Framework for Slice Creation and Deployment Using Machine Learning	No	Yes	Limited dataset size and static network topology.
51	2023	Classification of broadband network devices using text mining technique	Yes	Yes	Limited dataset size and performance variation across algorithms.
52	2023	Deep-Learning-Based Classification of Digitally Modulated Signals Using Capsule Networks and Cyclic Cumulants	Yes	No	Computational complexity and performance for specific modulations.
53	2023	EOG Signal Classification with Wavelet and Supervised Learning Algorithms KNN, SVM and DT	No	Yes	Limited data size and performance variation across algorithms.
54	2023	Quality of service management in telecommunication network using machine learning technique	No	Yes	Limited data and false positives/negatives.

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons
55	2023	Machine Learning Technique In Qos Management Network	No	Yes	Limited scope and threshold dependence.
56	2023	MLPRS: A Machine Learning-Based Proactive Re-Routing Scheme for flow classification and priority assignment	No	Yes	Limited dataset and computational overhead of classification.
57	2021	Application of machine learning methods for automated classification and routing in ITIL	Yes	Yes	Data dependency and interpretability.
58	2023	A Comprehensive Survey on Machine Learning using in Software Defined Networks (SDN)	Yes	Yes	Data dependency and computational complexity.
59	2022	Top-Down Machine Learning-Based Architecture for Cyberattacks Identification and Classification in IoT Communication Networks	Yes	No	High computational complexity and limited validation.
60	2021	Neural Network aided Optimal Routing with Node Classification for Adhoc Wireless Network	Yes	No	Limited dataset and computational complexity.

A comprehensive examination was performed on studies numbered 31 through 60, comprising a total of 30 studies, as evidenced by the results. Each study was assessed to ascertain the necessity for optimisation in two distinct domains: deep learning methodologies and data labelling procedures. Study number 31, conducted in 2021, titled "Network Traffic Classification Using Deep Convolutional Recurrent Autoencoder Neural Networks for Spatial-Temporal Features Extraction," needs to be optimised in deep learning to handle the overlapping network configuration classifications. Study 32 of 2020, titled "Network Intrusion Detection System: A Systematic Study of Machine Learning and Deep Learning Approaches," requires optimisation in both deep learning and data labelling. This is necessary because the model is quite complex and there are concerns with class imbalance. The results indicate that deep learning optimisation is required in 87% of the trials, specifically 26 out of 30. This significant percentage highlights the extensive requirement for enhancements in computational complexity, model performance, and management of specific data features in these investigations. For instance, research papers such as study 45 published in 2024, titled "Multi-Stage Learning Framework Using Convolutional Neural Network and Decision Tree-Based Classification for Detection of DDoS Pandemic Attacks in SDN-Based SCADA Systems," emphasise the need for optimisation because of the high computational expenses and the limited sizes of the datasets.

Conversely, 60% of the investigations (18 out of 30) necessitate optimisation of data labelling. This is crucial for tackling the limits of the dataset, fixing the imbalance in class distribution, and assuring the use of high-quality training data. Study number 50 from 2023, titled "An E2E Network Slicing Framework for Slice Creation and Deployment Using Machine Learning," needs to improve data labelling because of a small dataset and a fixed network structure. Subsequently, in the final test, an analysis was conducted on the latest 10 studies, bringing the total number of studies tested to 70 regarding deep learning. The results are presented in Table 4 below.

Table 4. Analysis Review of Studies Numbered 61 to 70 Regarding the Need for Optimization

No.	Year	Title	Needs Deep Learning Optimization	Needs Data Labeling Optimization	Reasons

61	2023	Traffic Classification in IP Networks Through Machine Learning Techniques in Final Systems	No	Yes	The research primarily focuses on classical machine learning algorithms, and additional features like flow duration and speed could enhance accuracy.
62	2021	Machine Learning Techniques for Network Analysis	Yes	No	The study uses ANN with potential LSTM for future work, suggesting exploration into deep learning techniques could improve accuracy.
63	2023	Machine Learning Approach on Multiclass Classification of Internet Firewall Log Files	No	Yes	The focus is on traditional machine learning methods, and exploring deep learning models could be beneficial. Addressing class imbalance is also suggested.
64	2021	Quality-of-Service Performance Comparison: Machine Learning Regression and Classification Based Predictive Routing Algorithm	No	Yes	Limited network environment and classification errors suggest room for exploring deep learning methods and addressing class imbalance.
65	2023	Vehicle Routing Problem Optimization with Machine Learning in Imbalanced Classification Vehicle Route Data	No	Yes	Focus on KNN for classification; exploring real-time data integration and deep learning methods could improve model accuracy and generalizability.
66	2022	A Decision Tree-Based Online Traffic Classification Method for QoS Routing in Data Center Networks	No	Yes	While decision trees are used, exploring deep learning for handling unknown traffic types and larger datasets is recommended.
67	2021	Traffic Classification for Efficient Load Balancing in Server Cluster Using Deep Learning Technique	Yes	No	Lack of details about the deep learning model and limited evaluation suggest further exploration and detailed assessments are needed.
68	2023	GRADE: Deep Learning and Garlic Routing-Based Secure Data Sharing Framework for IIoT Beyond 5G	Yes	No	Promising results with LSTM, but further real-world testing and computational efficiency optimization are needed.
69	2022	Deep Learning for Encrypted Traffic Classification and Unknown Data Detection	Yes	No	The focus on DNN for fine-grained activity detection suggests exploring further optimization and comparison with other models.
70	2021	High Accuracy WiFi-Based Human Activity Classification System with Time-Frequency Diagram CNN Method for Different Places	Yes	No	Limited dataset and static environment assumption suggest room for exploring larger datasets and dynamic environments.

The findings from the final examination (61-70), which examined the most recent 10 research, indicate that 60% (6 out of 10) of them necessitate optimisation of deep learning, while 70% (7 out of 10) require optimisation of data labelling. Deep learning optimisation is necessary to tackle a range of problems. Study number 62 conducted in 2021, titled "Machine Learning Techniques for Network Analysis," proposes that incorporating sophisticated deep learning techniques such as LSTM, in addition to the use of ANN, might greatly enhance accuracy. Study 67 from 2021, titled "Traffic Classification for Efficient Load Balancing in Server Cluster Using Deep Learning Technique," highlights a deficiency in the thorough evaluation of the deep learning model. This suggests the necessity for additional investigation and comprehensive assessments to improve its performance. However, optimising data labelling is crucial for addressing issues associated with constraints in datasets and imbalances in class distribution. As an illustration, research paper 63 from 2023, titled "Machine Learning Approach on Multiclass Classification of Internet Firewall Log Files," emphasises the emphasis on conventional machine learning techniques and the necessity of tackling class imbalance in order to enhance the model's efficacy. According to study number 66 from 2022, titled "A Decision Tree-Based Online Traffic Classification Method for QoS Routing in Data Centre Networks," the authors propose that although decision trees are employed, the utilisation of deep learning techniques could potentially enhance the handling of unknown traffic kinds and larger datasets. To summarise, 60% of the research necessitate the optimisation of deep learning techniques in order to boost computational efficiency, enhance model performance, and effectively handle specific data features. However, 70% of the studies require data labelling optimisation in order to address the limits of the dataset, achieve a balanced distribution of classes, and ensure the training data is of good quality. Optimisations play a vital role in improving the accuracy and dependability of research outputs, while also guiding future research upgrades.

4 Conclusion

Analysis of 70 research indicated that 60% of the studies necessitate optimisation of deep learning, whereas 67.14% necessitate optimisation of data labelling. These percentages highlight substantial potential for enhancement in both deep learning approaches and data labelling procedures. Deep learning optimisation is essential in network QoS (Quality of Service) classification due to many factors. A significant obstacle often encountered in deep learning models is the high computational complexity, which necessitates a considerable amount of processing resources. Improving the optimisation of these models can increase their efficiency and scalability. Furthermore, it is of utmost importance to enhance the performance of the model by adjusting hyperparameters, refining network designs, and incorporating sophisticated techniques such as transfer learning. Furthermore, deep learning models must be capable of managing particular data attributes, such as temporal interdependencies in network traffic. Methods such as LSTM (Long Short-Term Memory) networks are frequently recommended to more effectively capture these interdependencies. The importance of optimising data labelling is evident from the fact that 67.14% of research indicate a need for enhancements in this aspect. Class imbalance is a common problem that occurs when certain classes are not adequately represented in the training data. It is crucial to address this issue by employing strategies such as oversampling, undersampling, or synthetic data synthesis. The datasets utilised in these investigations frequently require improvement in terms of their quality and comprehensiveness. Utilising datasets that are more varied and inclusive can contribute to the development of models that are more universally applicable. Ensuring precise and uniform labelling of data is also essential for optimal model performance. Enhanced data labelling procedures and validation processes are crucial for minimising noise and errors in the training data. Suggestions for future study involve integrating advanced deep learning approaches, such as investigating more intricate models and optimisation strategies to improve performance. Enhancing data labelling procedures through the creation of reliable methodologies and the use of larger and more varied datasets can effectively tackle existing constraints and enhance the training of models. Performing thorough empirical testing and validation can aid in comprehending the practical feasibility and efficacy of these models in various network settings. In addition, effectively executing solutions to address class imbalance might result in more precise and dependable classification results. Future research can enhance the quality and dependability of network services by addressing the highlighted demands for deep learning and data labelling optimisation, which will contribute to more effective and efficient network QoS classification systems.

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