

# Machine learning centered energy optimization in mobile edge computing: a review

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## ABSTRACT

Current literature reviews on machine learning-based approaches for mobile edge computing (MEC) energy optimization often lack in-depth gap analysis and fail to identify trends or offer actionable insights. Most focus narrowly on comparing MEC frameworks without critically evaluating or benchmarking prior research. This review contributes by addressing these gaps via analysis of existing reviews and related studies, with a focus on ML models, research objectives, evaluation metrics, datasets, tools, and gap identification. The review method follows a systematic literature review (SLR) using the PRISMA framework for transparency and reproducibility. Key findings reveal persistent challenges in energy consumption, computational overhead, cost, and poor performance in accuracy, QoS, latency, scalability, and carbon footprint. Deep reinforcement learning (DRL) emerges as the most commonly used model (55%), while TensorFlow (35%) is the most adopted tool, valued for its flexibility and robust community support. The AudioSet dataset is frequently used (28%) due to its compatibility. However, methodology limitations include dependency on study quality and exclusion of grey literature, context sensitivity. The review concludes by recommending advanced solutions such as serverless computing, liquid cooling, containerization, software-defined power, quantum computing, and blockchain to drive future MEC energy optimization.

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## 1. INTRODUCTION

Mobile computing background basics involve accessing and processing information on portable devices like laptops, tablets, and smartphones. As these device usages increase, their energy consumption also increases, impacting user experience and the environment [1], [2]. Currently, the global mobile device market is estimated at 20 billion and projected to reach 50 billion by 2030, with over 8 million global mobile applications. Mobile devices contribute 3-4% of total electricity consumption, significantly impacting global carbon emissions [3], [4]. The current frameworks suffer gaps such as high computational demands, lack of delay and accuracy assessments, high computational costs, and insufficient continuous state space optimization. Single-user scenarios, absence of hyperparameter tuning, privacy concerns, and limited exploration of alternative methods are among the related works gaps. Additionally, increased energy consumption in edge servers and a lack of consideration for cutting-edge technologies like quantum computing remain significant challenges.

Table 1 presents an overview of some of the previously published literature reviews on machine learning (ML)-based mobile edge computing (MEC) energy optimization approaches comparable to our proposed review. The limitations of these literature reviews include a lack of in-depth gap analysis of machine learning-based approaches for MEC energy efficiency optimization, with limited or no comparison in terms of models adopted, contributions or performance, evaluation metrics, identified gaps, machine learning tools, and datasets. The related literature reviews lack the deduction of trends, patterns, and insights from the reviewed literature. In addition, the current literature reviews do not review and make a comparison of other literature review articles but compare only similar frameworks on MEC energy optimization. The proposed framework fills these gaps by systematically analyzing ML techniques, datasets, and tools for MEC energy optimization, offering new insights into trends and providing guidance for future research.

Table 1. Literature reviews on ML-based MEC energy optimization frameworks

Author/Year	Objective	Models	Dataset source	Contributions	Limitations and gaps
Grzesik and Mrozek [5] (2024)	Review on combining ML with MEC for latency reduction and energy optimization	TensorFlow lite, PyTorch mobile	IoT datasets and edge computing platform data	Reduced data transmission, improved scalability, and latency	Limited comparative analysis; no comparison with other literature reviews
Asghari and Sohrabi [6] (2024)	Comprehensive survey on server placement in MEC, fog and cloudlet paradigms	Heuristic and ML optimization, evolutionary techniques	Cloud simulation datasets for server placement	Detailed review of optimization methods for efficient server placement and energy-saving strategies	Limited comparison of performance and models limited deduction of trends, patterns, and insights
Zhen <i>et al.</i> [7] (2024)	Proposal for an air-ground collaborative MEC architecture for 5G/6G	Reinforcement learning (RL), UAV-enabled ML models	5G & 6G deployment data; edge simulations	Efficacy of air-ground integration in meeting computational and connectivity demands	Lack of in-depth gap analysis, Inadequate model comparison, and Limited gap analysis
Alsadie <i>et al.</i> [8] (2024)	Review of AI techniques for resource management in fog computing	Deep Learning, Reinforcement learning (RL), Meta-Heuristics	Fog computing datasets; simulation data	Explores DL and RL's potential for energy optimization and load balancing in a fog	Incomplete comparative analysis, limited gap analysis, and no literature review benchmarking
Choudhury <i>et al.</i> [9] (2024)	Survey on ML-based computation offloading in MEC: latency sensitive applications	DNN reinforcement learning, supervised learning	IoT datasets, mobile edge computing simulation datasets	Optimized computation offloading and reduced energy consumption	Lacks detailed performance benchmarks across ML models. No comparison with other literature reviews
<i>Proposed (This Review)</i>	<i>Comprehensive, comparative, qualitative, Systematic, &amp; graphical analytical review of ML-based MEC Frameworks</i>	<i>DRL, DNN, Random Forest, Recurrent Neural Networks</i>	<i>Audioset Human Agents Vehicle datasets instances</i>	<i>Comparative &amp; Qualitative Analysis of key trends, gaps, tools, metrics, guidance</i>	<i>Exclude non-English studies, focus on structured data, and overlook valuable unstructured sources</i>

With the existence of unsolved issues in previous literature reviews, there is a need for a comprehensive, comparative, and analytical review of ML-based MEC energy optimization frameworks. This research will aim to address the shortcomings of earlier literature reviews by performing a comprehensive literature review with critical analysis, discussions, comparisons, interpretations, then deducing trends, patterns, and insights, and graphically summarizing the key findings together with finding ramifications and stating the research's handiness in the future. Furthermore, as the paper focuses on ML techniques, comparative analysis of the models, gaps, objectives, tools, datasets, contributions, and performance of various Machine Learning techniques are summarized in tabular form. Finally, the article offers some potential future research directions in machine learning-based IHD prediction. Below are the contributions of this research work:

1. Comprehensive comparative analysis of ML models - This review thoroughly compares popular ML models, such as deep reinforcement learning, random forest, recurrent neural networks, assessing their strengths, limitations, and guiding researchers in selecting suitable models for MEC optimization.

2. Qualitative analysis of key trends and gaps - The review identifies recurring gaps from literature like high energy consumption, lack of hyperparameter tuning, poor metric performance (accuracy, delay), high cost and privacy issues.
3. Identification of most adopted tools and metrics - This review extracts commonly used tools (TensorFlow, Keras, Matlab) and evaluation metrics (energy consumption, accuracy, delay), offering guidance on which to adopt by future researchers on MEC optimization.
4. Guidance for future research directions - The review suggests integrating explainable AI techniques for transparency and federated learning for data privacy, enhancing model reliability, interpretability, and ethical applicability, thereby advancing the clinical relevance of ML models in IHD prediction.

The structure of this article is as follows: Section 1 presents the Introduction which entails the research gap and contributions. Section 2 presents the review research approach, including the systematic literature review (SLR) methodology and related works on the latest ML-based energy efficiency techniques in MEC. Section 3 presents the results and discussions of the reviewed frameworks. Section 4 offers conclusions drawn from the study.

## 2. METHOD

### 2.1. Literature review methodology approach

This review adopts a SLR methodology adopted in [10] to ensure a comprehensive, unbiased analysis of existing ML frameworks applied to MEC energy optimization. The systematic approach incorporates both established review practices and recent advancements in ML research to address the research questions and gaps identified in the Introduction section, guiding the reader logically into the Results section. The SLR’s PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach, as shown in Figure 1, was chosen due to its structured, replicable nature, allowing for a consistent assessment across multiple studies and enabling a clear synthesis of trends, insights, and patterns in ML applications. PRISMA ensures transparency, reproducibility, and rigorous reporting of findings. The inclusion of visual summaries like pie charts supports this justification, offering a clear and evidence-based foundation for understanding ML’s potential in MEC optimization and guiding future research in this domain.

Figure 1 illustrates the PRISMA flow diagram for the SLR on ML-based MEC energy optimization. The review followed a structured methodology, identifying 1,490 articles published for the past 5 years from reputable databases such as IEEE Xplore, ScienceDirect, SpringerLink, and others. Keywords like "machine learning," "energy optimization," and "mobile edge computing" were used to refine the search. After applying inclusion and exclusion criteria, 230 articles were shortlisted for further evaluation. Initial screening excluded 1,260 articles due to irrelevance to ML or MEC energy optimization. A detailed review further excluded 207 articles for reasons such as lack of clear methodologies or absence of performance metrics. Data extraction followed, gathering essential information on authors, publication year, ML models, research objectives, evaluation metrics, limitations, datasets, and tools, which reduced the articles further to 23 finally articles included at the end. These were analyzed to extract key insights, trends, and gaps in ML techniques for MEC energy optimization, providing a comprehensive understanding of the field and directions for future research. This systematic methodology ensured clarity and reproducibility, offering a well-defined framework for advancing future research in ML applications for MEC energy optimization.

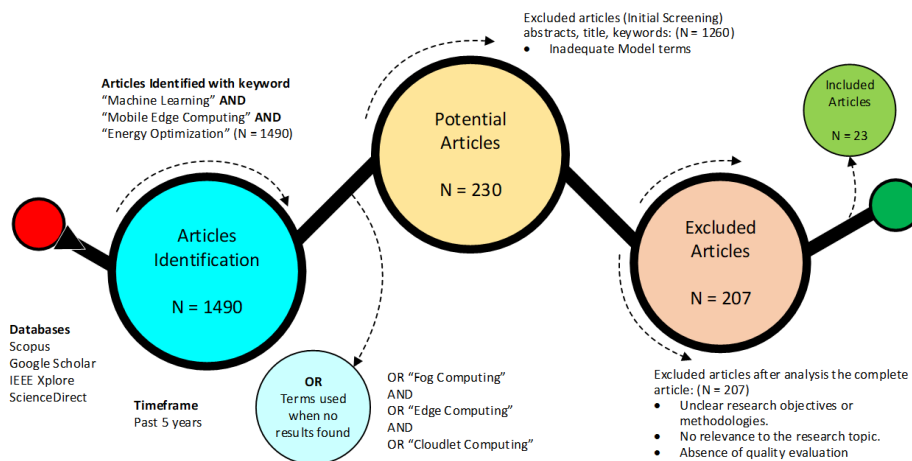


Figure 1. The proposed SLR PRISMA flow diagram

### 2.1.1. Limitations of the literature review methodology approach

The research method limitations typically include study quality, incomplete literature coverage, contextual variation, and practical applicability. While the PRISMA-guided systematic literature review provides a transparent analytic framework, its conclusions depend heavily on the integrity and depth of the studies that are published. Industry reports or grey literature that remain unindexed in the chosen databases are thus at risk of being overlooked. Moreover, results originating from controlled academic settings may generalize poorly to the wide range of real-world mobile-edge-computing contexts, particularly when data fidelity, network infrastructure, and deployment conditions vary. Therefore, any attempt to translate these findings into MEC energy-optimization practice warrants additional empirical testing to ensure relevance and effectiveness.

### 2.2. Machine learning based mobile edge computing energy optimization approaches

Table 2 provides a structured summary of 10 selected articles from the final pool of 23, specifically focusing on ML-based energy optimization in MEC. Key details, including author names, publication year, research objectives, ML models, evaluation metrics, datasets, tools, and identified limitations, are organized in a tabular format to enable detailed analysis. The selection process followed the PRISMA methodology, ensuring the inclusion of high-quality studies relevant to energy optimization in MEC through machine learning techniques. This table is analysed in detail in the results and discussions section.

Table 2. Related works on machine learning based on energy efficiency in mobile edge computing

	Authors and Year	ML model	Research objective	Evaluation metrics/performance	Model limitations	Datasets and tools
1	Malta <i>et al.</i> (2023) [11]	Reinforcement learning model	Sleep mode technique to monitor traffic at the base station	Energy consumption (80%), delay (46%)	Poor hyperparameter tuning, poor metric performance	Dataset: not specified, ML tool: Python 3.6
2	Katoch <i>et al.</i> (2023) [12]	Deep reinforcement learning model	A policy gradient method for improving energy efficiency	Power consumption (44%), energy consumption (61%)	Only supports single object tracking, high cost	Dataset: TB-100, LaSOT, ML tool: tensorflow
3	Speckhard <i>et al.</i> (2023) [13]	Random forest model	Multi-objective neural architecture search to enhance accuracy and energy usage	Energy usage (8%), accuracy (0.94%), memory usage (0.03%)	Search computational burden, high energy consumption, poor metric performance	Dataset: AudioSet dataset ML tool: tensorflow
4	Guo <i>et al.</i> (2023) [14]	Deep reinforcement learning	Predict the current processor usage to prevent degradation	Energy consumption (8%)	High computation high energy consumption	AudioSet dataset ML tool: Pytorch and Gym
5	Tan <i>et al.</i> (2023) [15]	Deep reinforcement learning model	Optimize the MEC system's energy consumption while meeting a QoS	Delay (26%), Energy consumption (30%), Task completion rate (30%)	Does not test the accuracy, has high energy consumption, and is high cost	Dataset: 50 users and 5 servers ML Tool: Pytorch
6	Xiao <i>et al.</i> (2023) [16]	Reinforcement learning model (RL)	To optimize the partition point between the deep learning model and the edge server	Inference Latency (44.5%), Energy consumption (41.8%), utility (35.0%)	Increased energy consumption of edge servers. High cost and privacy issues	Dataset: 10 mobile phones and 3 servers, ML tool: AlexNet/VGGNet
7	Nduwezu <i>et al.</i> (2020) [17]	Random forest model	To enhance accuracy, memory and energy usage	Accuracy (94%), computation (3.6%), energy usage (25%)	Computational burden: accuracy is low. Poor energy optimization	Dataset: AudioSet dataset, ML tool: TensorFlow
8	Zhou <i>et al.</i> (2023) [18]	Deep reinforcement learning	Enhance the energy efficiency of cooperative computing	Energy efficiency (maximized by 53.3%)	Neglect accuracy, Privacy issues, scalability issues, and cost	Dataset: AudioSet dataset, ML Tool: PyTorch
9	Dudeja <i>et al.</i> (2022) [19]	Deep learning model	DL models for effective data integration and storage in a warehouse	Accuracy (98%), Sensitivity analysis (95%)	Does not preserve the privacy of the data or the users	MRI images, open MRI datasets, PyTorch
10	Puso <i>et al.</i> (2024) [20]	Machine learning based on cloud optimization	Machine learning base energy efficiency optimization techniques for cloud computing	Accuracy (90%), energy usage (13%), utilization (4%), SLA violation (4%),	Privacy is not addressed, scalability is not addressed	CloudSim dataset. Tools: Tensorflow

### 3. RESULTS AND DISCUSSIONS

This section integrates findings from Table 1, which examines previous literature reviews on ML-based MEC energy optimization, and Table 2, which compares specific ML models applied to MEC energy efficiency. The analysis discusses recurring trends, gaps, key insights, and implications for future research. The results of the findings are presented in graphs and discussed.

#### 3.1. Trends and insights: summary of findings

Table 1 highlights persistent limitations in prior literature reviews on ML-based MEC energy optimization. These include insufficient gap analysis, a lack of emphasis on datasets and tools, and minimal focus on performance benchmarks. For example, authors in [5] focused on combining ML and MEC for latency reduction and energy optimization but did not compare other literature reviews or provide a comprehensive performance analysis. Similarly, authors in [6] reviewed server placement techniques using ML but failed to deduce trends or provide insights on dataset diversity or model applicability. Across these reviews, there is a limited emphasis on integrating practical solutions for scalability, data privacy, and interpretability, key factors for real-world MEC adoption. The reliance on narrow datasets and a focus on isolated performance metrics, such as latency and energy consumption, further restricts the ability to generalize findings across diverse MEC scenarios.

Table 2 reveals specific insights into the application of ML models for MEC energy optimization. deep reinforcement learning (DRL) emerges as the most widely adopted model, accounting for 55% of the studies. Its popularity is attributed to its capacity for handling complex, dynamic environments and its adaptability to real-world challenges. Random Forest and Deep Learning models are used in 28% and 17% of studies, respectively, highlighting their effectiveness in achieving high accuracy and efficiency. Despite these strengths, the computational demands and "black box" nature of these models hinder their broader adoption in MEC systems. The dominant research gap from the literature was the high energy consumption, framework delays, and accuracy issues, all amounting to 16%. These limitations were accompanied by issues concerning high costs and unproven model accuracy. In addition, Tensorflow was the most used tool in the studies, accounting for 35% due to its flexibility, expansiveness, and strong backing from the community. The AudioSet dataset was the most adopted in 28% of the studies due to its compatibility with ML systems.

#### 3.2. Descriptive visual analysis: detailed interpretation of related frameworks (Table 2)

##### 3.2.1. The most adopted ML models from literature

Figure 2 shows the most adopted ML models from the literature for edge computing energy optimization. From the literature review, DRL, random forest (RF), reinforcement learning (RL), deep learning (DL), and recurrent neural networks (RNN) were among the machine learning models adopted in the literature with 55% of related works using DRL model to solve energy efficiency problems in mobile computing. Followed by Deep Learning with 14% and Reinforcement Learning at 9%. DRL is the most widely used model because, in comparison to other models, DRL excels in solving complex tasks, handling high-dimensional environments, learning useful data representations, interacting without supervision, and scaling for real-world problems.

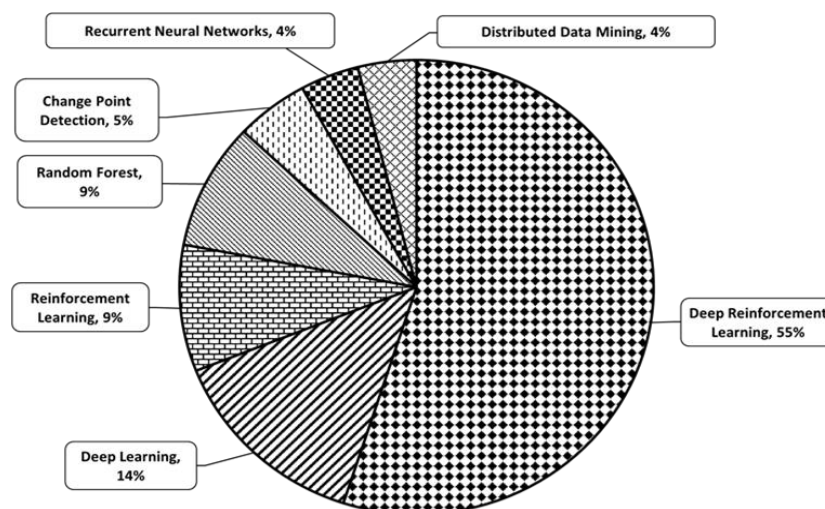


Figure 2. The most adopted ML model from the literature

**3.2.2. The most prevalent objectives from current approaches**

Figure 3 depicts an analysis of research articles from the literature that address the most common goals of using ML for mobile computing energy minimization. Figure 3 shows that the most dominant research objective is to reduce power or energy consumption by 52%. Aside from energy reduction, other objectives include memory optimization at 9%, delay minimization at 4%, task offloading at 5%, and many others. The primary reasons for reducing energy consumption as the dominant research objective in literature are that reducing energy consumption in mobile devices prolongs battery life, enhances usability and performance, mitigates environmental impact, improves resource utilization, and leads to cost savings for users and service providers.

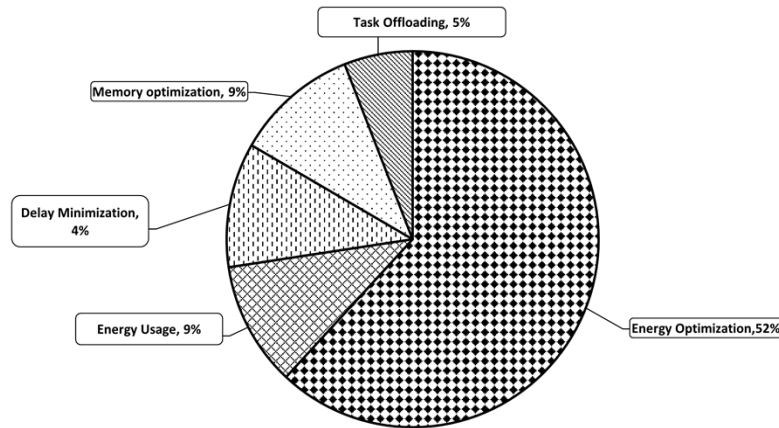


Figure 3. Most adopted research objectives from literature

**3.2.3. The most adopted ML datasets from literature**

Figure 4 depicts a summary analysis of the most widely used ML datasets in literature, with AudioSet datasets accounting for 28% of the total, followed by Sensor Instances by 11%. Other datasets were obtained from various sources and databases, and they accounted for 5% to 6%. The primary reasons for the AudioSet dataset's dominance in literature are that AudioSet, compatible with TensorFlow and PyTorch, allows researchers to use pre-trained models for sound recognition. It's publicly accessible, promoting accessibility and openness in research and development efforts related to audio and sound recognition [21]. Audioset is annotated with one or more labels corresponding to the sound events present in the clip, providing valuable data for training and evaluating machine learning algorithms [22].

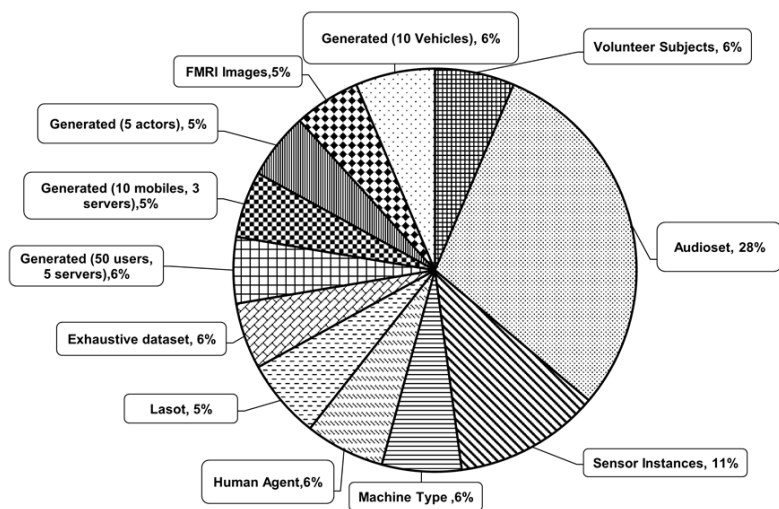


Figure 4. Most adopted ML datasets from literature

### 3.2.4. The most adopted ML model evaluation metrics from literature

Figure 5 shows a summary of the most adopted ML metrics from Literature Review with a larger percentage of 30% being dominated by Energy consumption, accuracy at 11%, delay at 9%, energy usage and latency at 5%, power consumption at 4%, memory usage at 4%, cost at 4% and many others. The most adopted metric is energy consumption (30%), followed by accuracy (11%), and the explanation for this is that, for energy consumption, the reasons are similar to why energy consumption is the dominant objective, and this was presented in the previous sections. The explanation for accuracy being the next dominant metric is that accuracy measures a model's performance; high accuracy indicates precise predictions, while low accuracy shows errors. Comparing accuracy helps assess model suitability, guiding parameter optimization, and enhancing overall performance during training [23].

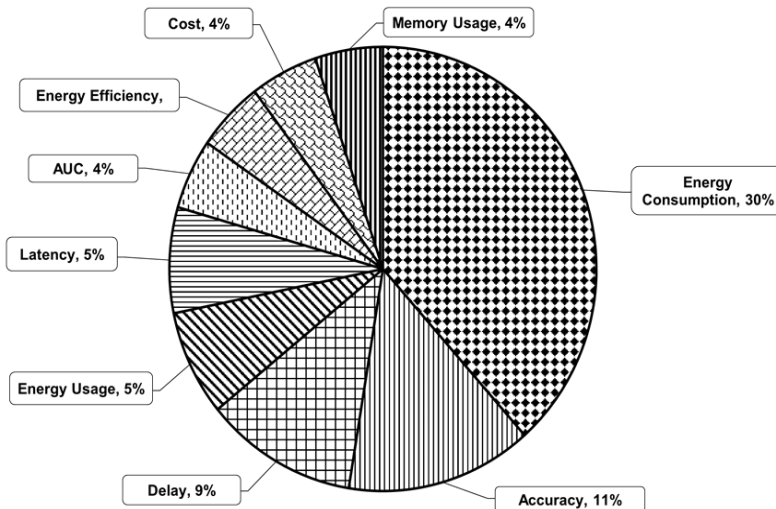


Figure 5. Most adopted ML metrics from the literature

### 3.2.5. The most prevalent limitations with the current approaches

Figure 6 shows a percentage summary of the most prevalent limitations of current ML-based approaches for mobile computing energy reduction. A larger portion of current literature approaches is being dominated by high computation (16%), Delay and accuracy of model not tested (16%), followed by high-cost problems at 11% and many more. High computation is a major limitation because scaling high-computation tasks is challenging due to growing data volumes and model complexities. Optimizing algorithms reduces computational burden, energy consumption, and environmental impact. Lengthy tasks delay research, hinder productivity, and incur significant resource costs. The lack of assessment regarding the delay and accuracy of the proposed models, as indicated by 16% of the literature in Figure 5, represents significant drawbacks in ML models aimed at reducing energy consumption in mobile computing. This limitation arises due to the following reasons: Without assessing delay and accuracy, researchers cannot accurately evaluate model effectiveness, leading to inaccurate conclusions and limited generalization. These metrics provide insights for optimization and improve model credibility and reliability [24].

### 3.2.6. Most adopted ML tools from literature

Figure 7 provides an overview of the most utilized ML tools for minimizing mobile energy consumption according to the literature. As depicted in the figure, the TensorFlow ML tool has been adopted by 35% of the current literature, followed by PyTorch at 30%. TensorFlow stands out as one of the most popular open-source machine learning frameworks available today due to its exceptional flexibility, scalability, and seamless integration with other software libraries [25]. These qualities distinguish it from other ML tools that have been examined, contributing to its widespread adoption in literature. TensorFlow seamlessly integrates with popular programming languages, offers scalability, and caters to a diverse array of tasks. Additionally, it benefits from a thriving developer community, ensuring the availability of abundant resources, and offers support for production environments, facilitating straightforward deployment and scaling processes [26].

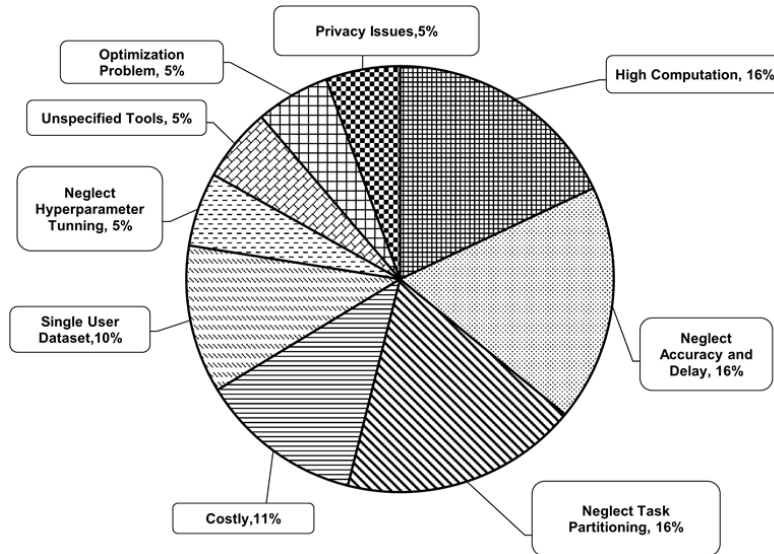


Figure 6. Most prevalent limitations with current approaches for cloud computing energy reduction

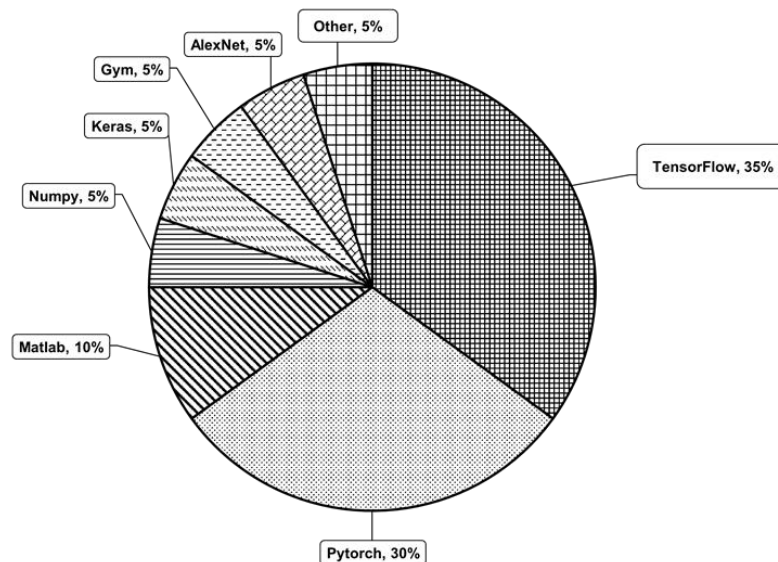


Figure 7. Most adopted ML tools from the literature for cloud computing energy optimization

### 3.2.7. Related works performance

Figure 8 shows the analysis of performance for reviewed frameworks that have considered energy consumption as a metric. The energy reduction values are reported (in ascending order as presented) are as follows: the lowest performance was achieved by Ali *et al.* [3] at 3%, Zhao and Zhou [27] at 7%, Speckhard *et al.* [13] obtained about 10%, Khan [26] *et al.* recorded approximately 18%, Ashiquzzaman *et al.* [25] obtained nearly 19%, Liu *et al.* [24] obtained approximately 20%, McClellan *et al.* [22] achieved about 28%, Tan *et al.* [15] reported approximately 30%, Mohanty *et al.* [4] achieved 36%, Chen *et al.* [2] achieved 38%, Xiao *et al.* [16] achieved approximately 42%, Zhou *et al.* [18] achieved about 55%, Culman *et al.* [1] achieved approximately 75%, Malta *et al.* [11] recorded nearly 80%. while the highest energy reduction performance recorded in the literature, Ale *et al.* [21], reached 95%. Based on the data presented in Figure 8, the average energy consumption performance is calculated to be 35%.

Figure 9 illustrates the performance analysis of frameworks reviewed, which have regarded accuracy as a metric. The accuracy values are reported (in ascending order as presented) are as follows: Nduwezu *et al.* [17] and Speckhard *et al.* [13] achieved accuracy of approximately 3%, Ali *et al.* [3]

achieved about 16%, Culman *et al.* [1] achieved 40%. The findings indicate that the highest accuracy performance documented in the literature, was 98% by Dudeja *et al.* [19] and Ashiquzzaman *et al.* [25]. According to the data presented in Figure 9, the average accuracy achieved is calculated to be 41.3%.

Figure 10 presents the performance analysis of frameworks reviewed, which have regarded delay as a metric. The delay values are reported (in ascending order as presented) are as follows: As per the figure Goulão *et al.* [28] obtained about 14%, McClellan *et al.* [22] achieved approximately 24%, Tan *et al.* [15] obtained around 27%, Zhou [27] achieved around 38% and findings reveal that the highest achieved value performance documented in the literature, as referenced by Malta *et al.* [11], reached 46%. Based on the data provided in Figure 10, the average delay achieved is calculated to be 29.2%.

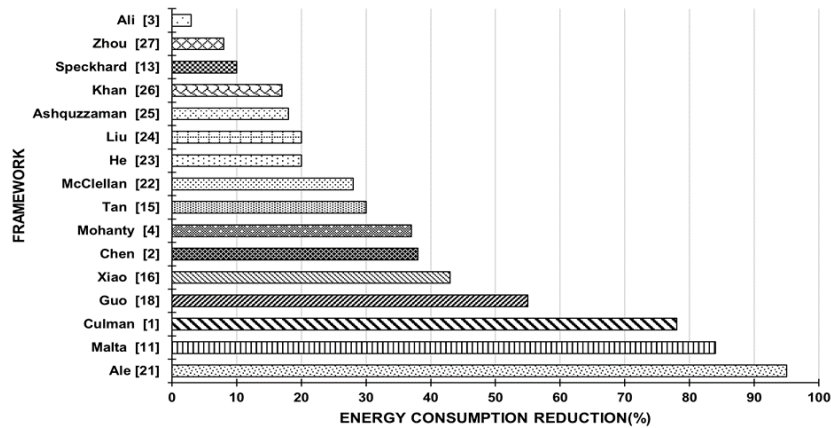


Figure 8. Performance analysis of related works based on the energy consumption metric

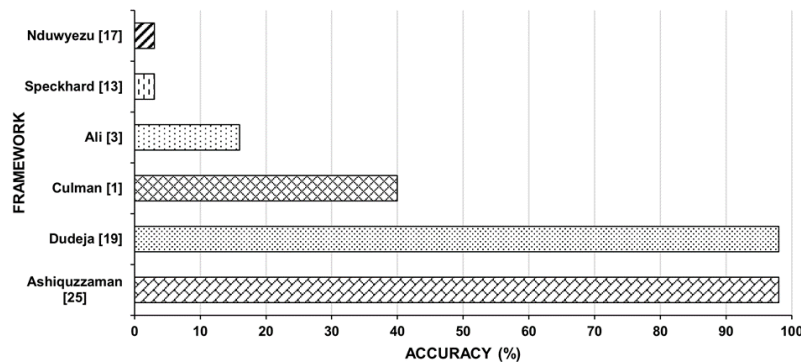


Figure 9. Performance analysis of related works based on the accuracy metric

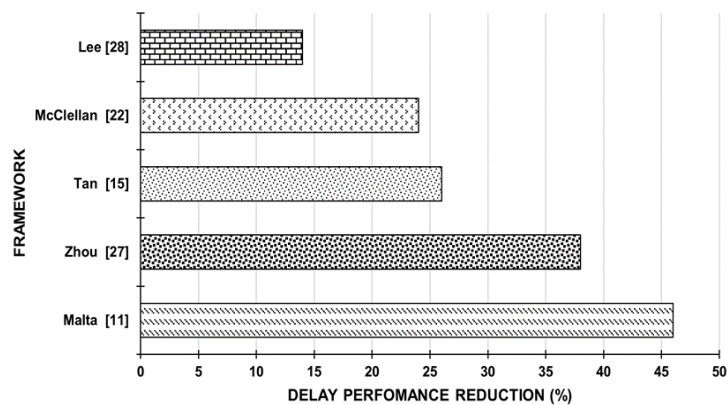


Figure 10. Performance analysis of related works based on the delay metric

#### 4. CONCLUSION AND FUTURE WORK

This study adopted the SLR method using the PRISMA framework for transparency and reproducibility and reviewed existing works on energy optimization in MEC using ML techniques, identifying critical gaps and areas for improvement. The findings revealed that paramount gaps are high energy consumption, delays, and accuracy issues, alongside problems of high costs, computational demands, and unproven model performance. Many prior reviews lacked in-depth analysis of gaps, datasets, tools, and evaluation metrics, with insufficient focus on practical issues such as scalability, privacy, and model interpretability. DRL emerged as the most adopted model in 55% of studies due to its adaptability and capacity to handle complex environments. However, its computational intensity and black-box nature hinder broader adoption. TensorFlow, used in 35% of studies, was the most popular tool due to its flexibility and robust community support, while the AudioSet dataset, featured in 28%, provided strong compatibility but limited diversity. Despite these advances, the lack of exploration of cutting-edge technologies like serverless computing, liquid cooling, and quantum computing persists. This review provides actionable insights, highlighting the need for scalable, privacy-preserving solutions and diverse datasets to advance ML-driven energy efficiency in MEC systems, bridging gaps and guiding future research directions. However, the PRISMA methodology has some limitations that include dependency on study quality and exclusion of grey literature, context sensitivity. The review recommends some potential cutting-edge energy optimization technologies, such as serverless computing, liquid cooling, containerization, software-defined power, quantum computing, and blockchain, that were not considered in current works.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

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I : **I**nvestigation

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E : Writing - Review & **E**ditng

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

#### CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

#### INFORMED CONSENT

Not applicable - this study did not involve human participants requiring informed consent.

#### ETHICAL APPROVAL

Not applicable - this study did not involve human participants or animals.

**DATA AVAILABILITY**





Data availability does not apply to this article as no new data were created or analyzed in this study.

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