Informatics Bulletin, Faculty of Computers and Artificial Intelligence, Helwan University
Published Online *Vol 7 Issue 2, July 2025*
(https://fcihib.journals.ekb.eg)

Meta-Learning in Real-Time Analysis: A Literature Review

Haitham Ghallab[1], Mona Nasr[1], Hanan Fahmy[1]
[1]Information Systems Dept., Faculty of Computers and Artificial Intelligence, Helwan University, Cairo, Egypt
haitham.ghallab@fci.helwan.edu.eg, drmona_nasr@fci.helwan.edu.eg, hanan.fahmy@fci.helwan.edu.eg

***Abstract*—As the demand for instantaneous decision-making continues to rise across various domains, real-time analysis has become a critical aspect of machine learning models in many real-world applications. Real-time analysis enables top managers to make informed decisions promptly and respond swiftly to changing risk factors, such as market fluctuations, cybersecurity threats, and customer preferences. Accordingly, researchers have tried to develop machine learning models with real-time capabilities, considering accuracy, model interpretability, and resource constraints. However, one significant challenge shows recent research focuses on implementing real-time models using common classification algorithms (such as logistic regression, decision trees, random forest, etc.) without considering the availability of the dataset required to train the models, especially in certain domains where training datasets is evolving and could be hard to be provided and that causes inaccurate results in severe areas such as healthcare and finance where inefficient insights are unforgivable. As a result, this research offers a comprehensive review to show the state-of-the-art techniques in meta-learning as an accurate and relevant solution for the above-mentioned challenge. The primary focus is the mechanisms that enable real-time models to dynamically adapt to new, unseen tasks with minimal data and computational resources. In addition, various meta-learning paradigms and their respective roles in improving real-time analysis performance are explored. Finally, emerging trends and future directions in the field are discussed, highlighting potential research avenues and the implications of meta-learning advancements for real-time systems across diverse domains, including finance, healthcare, IoT, and information security.**

***Index Terms*—Meta-Learning, Machine Learning, Real-Time Analysis, Finance, Healthcare, Information Security, IoT**

I. Introduction

REAL-TIME analysis refers to the process of gathering, processing, and interpreting data instantaneously or within a very short time frame. This type of analysis is crucial for applications where timely insights are necessary to make decisions that can significantly impact outcomes [1, 2]. Unlike traditional data analysis, which often involves batch processing and can tolerate delays, real-time analysis requires continuous data stream processing and rapid computation as shown in **Fig. 1.** In real-time analysis, data is captured from various sources such as sensors, logs, social media, and transactional systems as it arrives. This immediate data collection is followed by efficient data ingestion, which ensures that the data is transferred into a processing system without delay. Once ingested, the data undergoes processing where algorithms and models are applied to transform, analyze, and derive insights from the incoming information. Processed data is then stored for quick retrieval and further analysis. Finally, the insights gained from the data are presented through dashboards and visual tools that can be interpreted quickly by end-users. Unlike batch processing, real-time analysis relies on incremental or continual re-training which involves continuously updating the model over time as new data arrives. This is used in scenarios where the environment or data is constantly evolving, and the model needs to adapt to those changes to remain effective. It's common in real-time systems like recommendation engines, financial trading algorithms, or IoT systems [3].

Technologies that enable real-time analysis include stream processing frameworks like Apache Kafka [4] and Apache Flink [5], in-memory computing platforms such as Apache Ignite [6, 7], and event-driven architectures that ensure responsive data handling [8]. These technologies allow systems to handle high volumes of data with minimal latency, providing timely insights and enabling quick actions.

Real-time analysis is instrumental in identifying and mitigating risks as they emerge, by continuously assessing various risk factors, such as market fluctuations, cybersecurity threats, or regulatory changes, enabling top managers to implement proactive risk management strategies. Furthermore, Real-time analysis can identify areas where resources are underutilized or can be reallocated for better efficiency, this leads to cost reduction and optimal allocation of resources, ultimately contributing to improved financial performance. Finally, Real-time analysis has widespread applications across various industries, enhancing decision-making processes and operational efficiency.

Despite its advantages, real-time analysis poses several challenges, especially when dealing with special cases and new unseen tasks [9, 10]. Accordingly, in such rare cases, considering dataset availability is crucial to train models and predict accurate insights ahead of time. Recent research focuses on implementing real-time models using common classification algorithms (such as logistic regression, decision trees, random forest, etc.) without considering the availability of the dataset required to train the models, especially in certain domains where training datasets could be hard to be provided and that causes inaccurate results in severe areas such as healthcare, information security, and financial sectors where bad insights are unforgivable, that occurred because these models start building from scratch, without building on experience and reusing prior skills gained from similar tasks, which would make acquiring new skills easier with fewer examples and less trial-and-error. As a result, robust infrastructure and efficient processing algorithms are required to manage unseen tasks with minimal data effectively [9, 10].

This research is divided into four sections, section one focuses on the background and fundamental concepts of meta-learning and real-time analysis as distinct concepts, including their definition, objectives, methodologies, categories, and recent models. Section two covered the significance of integrating meta-learning with real-time capabilities by presenting recent meta-learning real-time models and highlighting the added value across various domains. Finally, sections four and five addressed the limitations, open challenges, and future directions associated with these emerging models.

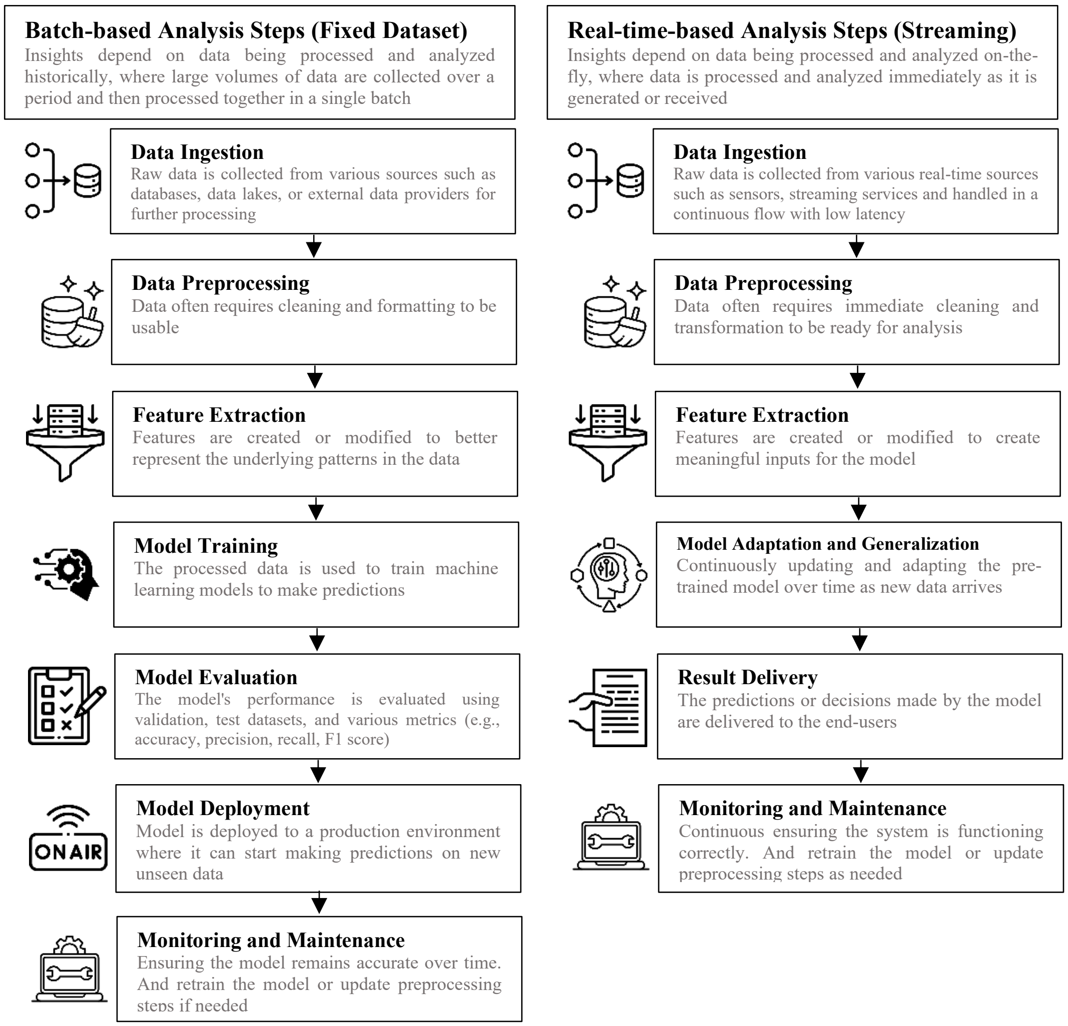

Fig. 1. Batch-based Analysis vs Real-time-based Analysis

II. BACKGROUND AND FUNDAMENTAL CONCEPTS

Top managers in many critical sectors especially in healthcare, information security, and finance depend heavily on real-time models to help them make important decisions, where any inaccurate insights generated due to the lack of training dataset could cause severe losses to the business, so meta-learning is proposed as an efficient solution to avoid these losses and to help managers to make the most valid actions.

A. Meta-learning

Meta-Learning is a specialized area within machine learning sector and focuses on learning how to learn. Instead of directly learning a task, meta-learning optimizes the learning process itself, enabling models to generalize across various tasks and adapt quickly with minimal data. In essence, meta-learning targets improving the effectiveness of the learning process, making it relevant for situations requiring rapid adaptation or multi-task learning [11], **Fig. 2.** illustrates the connection between machine learning (ML) and meta-learning.

Acquiring new skills is rarely a process that starts from scratch. New skills are often built on related tasks, leveraging previously successful strategies and focusing on what experience suggests is worth exploring [11, 12]. Each skill learned makes acquiring additional skills easier, requiring fewer examples and less trial-and-error. Essentially, individuals develop the ability to learn across tasks. Similarly, when creating machine learning models for a specific task, insights from related tasks or prior understanding of machine learning behaviors often inform better decision-making [11, 12].

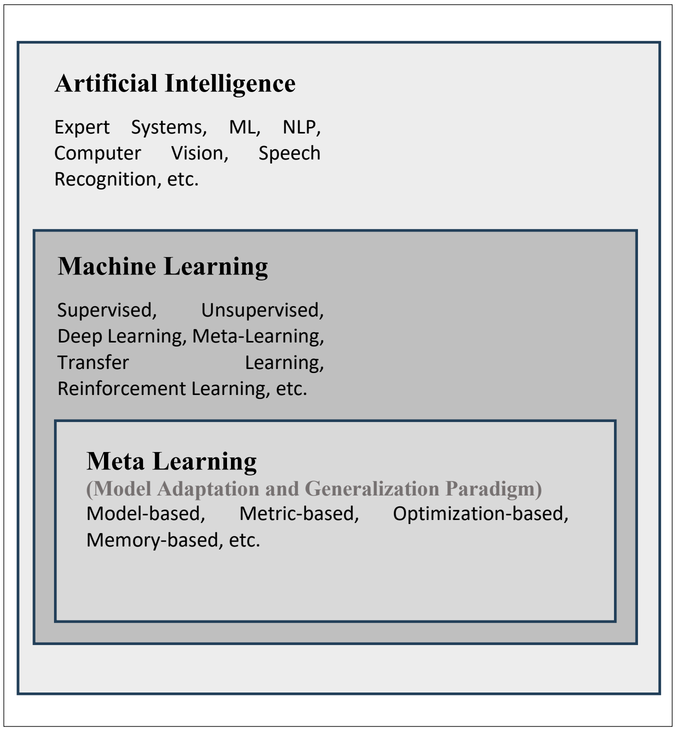

Fig. 2. Meta-Learning for Adapting and Generalizing Machine-Learning Models

The goal of meta-learning is to systematically harness prior experience in a data-driven manner. This process begins with collecting meta-data, as shown in **Fig. 3**. which outlines previous learning tasks and models. Meta-data includes algorithm configurations, such as hyperparameter settings, pipeline compositions, or network architectures, along with model evaluations like accuracy and training time, learned parameters like neural network weights, and measurable task properties, known as meta-features. The next step involves using this meta-data to extract and transfer knowledge that helps guide the search for optimal models for new tasks.

1) Meta-Learning Main Objectives

Meta-learning aims to create systems that can "learn how to learn" by quickly adapting to new tasks, generalizing across different tasks, and efficiently managing resources. The term meta-learning covers any type of learning based on prior experience with other tasks, the more similar those previous tasks are, the more types of meta-data can be leveraged, and fortunately, in real-world tasks, there are plenty of opportunities to learn from prior experience. As a result, the key objectives of the meta-learning are structured around optimizing the learning process and improving model performance in various conditions, and the key objectives include:

- *Rapid Adaptation* plays a critical role in meta-learning, where models must quickly adjust to new tasks, often under constraints of limited data and computational resources [13].
- *Generalization Across Tasks* in meta-learning emphasizes the ability to apply previously acquired knowledge to enhance model performance on new, related tasks [15].
- *Automating the Learning Process* focuses on minimizing the need for human intervention in critical processes such as model selection, hyperparameter tuning, and algorithm selection [14].
- *Improved Few-Shot Learning* is a crucial component of meta-learning that enables models to perform well on new tasks with only a limited number of labeled examples [16].
- *Task-Specific Customization* One-size-fits-all approaches are often insufficient for tasks with unique requirements, and meta-learning offers a way to create customized learning strategies tailored to individual tasks [13].
- *Learning Efficient Optimizers* enhance the efficiency of model optimization. Instead of relying on traditional optimization methods, the goal of meta-learning is to develop optimizers that adapt according to the task and the learning progress [17].
- *Scalability and Robustness* is a critical factor in ensuring that meta-learning algorithms can effectively manage increasingly complex tasks while maintaining efficiency and performance [18].

This detailed explanation delves into each objective of meta-learning and highlights the specific mechanisms that contribute to achieving these goals. By focusing on these objectives, meta-learning systems can become more adaptable, efficient, and scalable, making them well-suited for real-time analysis and dynamic environments.

2) Meta-Learning Approaches

There are different approaches used to implement meta-learning models, and choosing the optimal approach depends on several factors, including the nature of the tasks, the available data, computational resources, and specific goals of the learning process. The most common meta-learning approaches are:

- *Model-based approach* focuses on learning an initialization of parameters that can be rapidly adapted to new tasks. This approach is highly effective for fast adaptation in few-shot learning scenarios, where only a few examples are available for training. Examples of model-based approaches include MAML (Model-Agnostic Meta-Learning) and Reptile. However, these methods may struggle when tasks are highly diverse, requiring careful tuning to generalize effectively across tasks [13].
- *Metric-based approach* uses a learned similarity measure or distance metric to compare new tasks with previously learned tasks. This approach is particularly useful for few-shot classification, where models classify new examples based on their similarity to existing ones. Examples include Matching Networks and Prototypical Networks. While metric-based methods are known for producing interpretable distance metrics, they may not scale well to very large datasets and are limited by the quality of the learned metric [19].

- *Optimization-based approach* improves the efficiency of the learning process by learning the optimization algorithm itself. This approach is flexible and can be applied to a wide range of tasks. Notable examples include the LSTM Meta-Learner and Meta-SGD. Despite its benefits, optimization-based meta-learning can be computationally expensive and may require large amounts of data to be effective [31].
- *Memory-based approach* uses memory-augmented neural networks to store and retrieve information from past tasks, facilitating faster adaptation to new ones [20]. This approach is particularly well-suited for sequential learning and time-series tasks. However, implementing memory-based models can be complex, and efficient memory management is often challenging. Examples of memory-based approaches include Neural Turing Machines and Memory-Augmented Networks [21].
- *Reinforcement learning-based (RL-based) approach* frames meta-learning as a reinforcement learning problem, where an agent learns a policy to adapt to new tasks by interacting with its environment [22]. This approach is highly effective for tasks with clear reward signals and is adaptable to dynamic environments. Meta-RL (Meta-Reinforcement Learning) is a well-known example. However, RL-based meta-learning is computationally expensive and often requires extensive exploration to identify optimal policies [23].
- *Latent Space Optimization (LSO-based) approach* optimizes a model by searching within a latent space where each point represents a potential solution. This method enables efficient search and adaptation for discrete and continuous optimization problems. LEO (Latent Embedding Optimization) is a notable example. The performance of LSO-based meta-learning depends heavily on the quality of the latent space representation, which can sometimes be a limiting factor [24].
- *Neural Architecture Search (NAS)-based approach* automates the design of neural network architectures by searching through a predefined space of possible architectures. This method can discover architectures that generalize well across tasks and reduces the need for human intervention. However, NAS-based methods come with high computational costs and require extensive evaluation of candidate architectures. An example of this approach is T-NAS (Task-Adaptive Neural Architecture Search) [25].

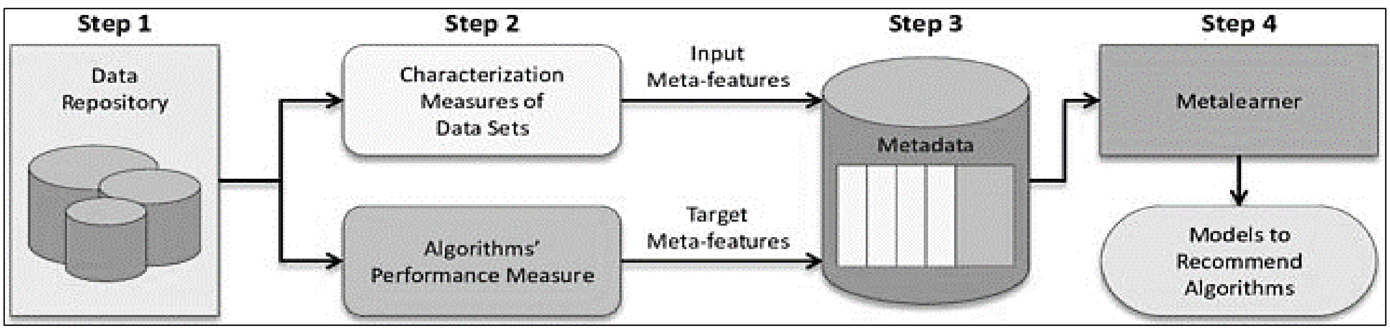

Fig. 3. Meta-Learning Dimensions [67]

The various approaches to meta-learning offer unique strengths and trade-offs, catering to different problem domains and task requirements. Model-based approaches are highly effective for rapid adaptation in few-shot learning scenarios, while metric-based methods excel in interpretability and classification based on similarity measures. Optimization-based approaches, though computationally demanding, provide flexibility and efficiency in the learning process. Memory-based techniques leverage past experiences effectively but come with implementation complexity, especially regarding memory management. RL-based approaches adapt well to dynamic environments with clear reward signals, but they require significant computational resources and exploration. LSO-based meta-learning offers efficient solutions for both discrete and continuous optimization, though its success heavily depends on the quality of latent space representations. Lastly, NAS-based methods automate the search for optimal neural architectures, reducing human intervention but often at the expense of high computational costs.

3) Meta-Learning Recent Models

Recently, many types of research presented different meta-learning models that shows different results in terms of performance, efficiency, scalability and applicability. Meta-learning models has seen significant advancements over the last decade. Several models have been proposed, each with unique approaches and advantages as shown in **Table 1.** Where, each of these models has its strengths and is suitable for different use cases and tasks depending on the specific requirements of performance, efficiency, scalability, and applicability, where in case of better performance: LEO, T-NAS, Meta-SGD, and SNAIL are noted for their high accuracy, particularly in specialized domains like few-shot learning and sequential tasks.

On the other hand, Prototypical Networks and Siamese Networks are among the most efficient in terms of training time. Plus, Prototypical Networks and LEO demonstrate excellent scalability to large datasets. Finally, MAML and Reptile offer broad applicability across various tasks, whereas specialized models like Meta-RL and SNAIL excel in their respective domains.

B. Real-Time Analysis

Real-time analysis or streaming data processing refers to the continuous processing and evaluation of data as it is generated, allowing for immediate insights and actions [35]. This involves the use of algorithms and models to analyze data streams, detect patterns, and make decisions with minimal latency. Real-time analysis is crucial in applications where timely information is essential, such as autonomous systems, financial trading, information security, healthcare monitoring, and industrial automation. The implementation of real-time analysis typically requires robust data infrastructure, efficient algorithms, and scalable computational resources to handle high-velocity data and ensure prompt response times [35].

TABLE I
META-LEARNING RECENT MODELS

Model	Performance (Accuracy)	Efficiency (Training Time)	Scalability (Large Datasets)	Applicability (Various Tasks)	Approach
MAML (Model-Agnostic Meta-Learning) [13]	High accuracy for few-shot tasks; effective adaptation to new tasks.	Moderate to high; requires multiple inner-loop optimizations.	Struggles with very large datasets due to computational cost.	Suitable for a wide range of tasks including classification and regression.	Model -based
Reptile [27]	Similar performance to MAML but with slightly lower accuracy in some cases.	More efficient than MAML; fewer inner-loop steps needed [26].	Better scalability than MAML but still challenging with very large datasets.	Applicable to various tasks but slightly less versatile than MAML.	Model -based
Matching Networks [28]	High accuracy for few-shot classification tasks; strong performance in image and NLP tasks.	Moderate; involves training a network to produce embeddings and an attention mechanism.	Limited scalability; can be computationally expensive for large datasets.	Primarily used for classification tasks, especially in few-shot settings.	Metric-based
Prototypical Networks [29]	High accuracy for few-shot classification; simple and effective approach.	Efficient; faster training compared to Matching Networks.	Moderate scalability; can handle larger datasets better than Matching Networks.	Mainly used for classification but can be extended to other tasks.	Metric-based
Siamese Networks [30]	High accuracy for verification tasks; effective for few-shot learning.	Efficient; involves training two identical networks.	Moderate scalability; can handle larger datasets with careful design.	Primarily used for verification tasks (e.g., face verification) and classification.	Metric-based
LSTM Meta-Learner [31]	High accuracy for tasks requiring learned optimization strategies.	Computationally intensive; training the LSTM can be slow.	Limited scalability due to high computational cost.	Applicable to tasks where learning the optimization process is beneficial.	Optimization-based
Meta-SGD [32]	High accuracy with adaptable learning rates; effective for various tasks.	More efficient than LSTM Meta-Learner; fewer parameters to learn.	Moderate scalability; better than LSTM Meta-Learner.	Versatile across different tasks including classification, regression.	Optimization-based
Neural Turing Machines (NTMs) [33]	High accuracy for tasks requiring memory-based adaptation; strong performance in sequential tasks.	Computationally intensive; managing external memory is complex.	Limited scalability: memory management is a bottleneck.	Suitable for sequential and time-series tasks, complex problem-solving.	Memory-based
Memory-Augmented Neural Networks (MANNs) [20]	High accuracy for tasks requiring extensive use of memory; effective in time-series analysis.	High; complex memory management increases training time.	Limited scalability due to high computational overhead.	Best suited for sequential tasks, time-series, and problems requiring memory recall.	Memory-based
SNAIL (Simple Neural Attentive Meta-Learner) [34]	High accuracy for few-shot tasks; combines convolutional and attentional mechanisms effectively.	Moderate; the combination of attention and convolution can be computationally intensive.	Moderate scalability; efficient but can become challenging with very large datasets.	Suitable for a wide range of tasks including classification and regression.	Combination of convolutional and attention mechanisms

Meta-RL (Meta-Reinforcement Learning) [22]	High performance in reinforcement learning tasks; adapts well to new environments [23].	High; reinforcement learning training times are generally long.	Limited scalability; high computational and sample efficiency requirements.	Suitable for various RL tasks, such as robotics, games, and autonomous systems.	RL-based
LEO (Latent Embedding Optimization) [24]	High accuracy for few-shot learning; leverages latent embeddings effectively.	Moderate; training involves learning latent embeddings which can be complex.	Better scalability due to latent space optimizations.	Effective in classification and few-shot learning tasks.	LSO-based
T-NAS (Task-Adaptive Neural Architecture Search) [25]	High accuracy by adapting architectures to tasks; effective in many scenarios.	High; NAS methods are generally computationally expensive.	Better scalability than some meta-learning methods but still challenging.	Broad applicability across various tasks due to adaptable architectures.	NAS-based

1) *Real-Time Analysis Approaches*

There are several approaches that enable the immediate processing and interpretation of data as it is ingested. And each approach has its own set of trade-offs and is chosen based on the specific requirements of the application, such as latency tolerance, data volume, and computational resources. These various approaches leverage different techniques, frameworks, and use cases, illustrating their application in diverse domains, and these approaches includes:

- *Stream Processing* focuses on continuously processing data streams as they occur. This approach utilizes techniques such as sliding windows, tumbling windows, and session windows, which allow for the aggregation of events over time or specific periods [4, 5].
- *Online Learning* models, by contrast, focus on continuous updates based on new incoming data. Techniques such as incremental learning and stochastic gradient descent (SGD) enable models to evolve and adapt in real time without retraining from scratch [36].
- *Event-Driven Architectures* represent another approach to real-time analysis, designed to trigger specific actions in response to events as they occur [4, 8].
- *Edge Computing* pushes real-time processing closer to the source of data generation, reducing the latency typically associated with centralized processing [37].
- *Hybrid Architectures* combine batch processing and real-time processing to achieve a balance between the two methods [5, 38].
- *Real-Time Data Visualization* focuses on providing immediate visual insights into streaming data [39, 66].

The diverse range of real-time analysis approaches discussed—ranging from stream processing to edge computing—highlights the adaptability and scalability of current systems in handling continuous, real-time data.

2) *Real-Time Analysis Recent Models*

Real-time analysis plays a critical role in numerous fields, particularly when integrated with advanced machine learning models. Many researchers have proposed models that leverage real-time analysis in conjunction with machine learning techniques, significantly enhancing the decision-making process compared to traditional approaches. Additionally, the application of real-time analysis models has expanded considerably across various domains, including manufacturing, information security, healthcare, agriculture, and education. These models are designed to process and analyze data instantaneously, enabling prompt decision-making and immediate actions.

In the healthcare sector, a study introduced a real-time visible monitoring technique for detecting and tracking the growth of fatigue cracks to ensure structural safety [42]. In 2021, experimental results demonstrated the method's effectiveness in predicting the path of crack growth, achieving a crack length measurement accuracy of 0.6 mm. A lightweight machine learning model, specifically a decision tree, also facilitated real-time crack detection. However, limitations in the crack dataset and minor influences led to some errors, which must be addressed in future research.

Furthermore, real-time analysis has been used to assist individuals with certain disabilities in communicating more effectively. In 2021, research introduced a streamlined gesture recognition model using YOLO (You Only Look Once) v3 and DarkNet-53 convolutional neural networks [46]. The proposed model operates without requiring additional preprocessing, image filtering, or enhancement. It excels in extracting features from the hand, achieving notable performance with the YOLOv3-based model, which achieved accuracy, precision, recall, and F-1 scores of 97.68%, 94.88%, 98.66%, and 96.70%, respectively.

Additionally, researchers proved that immediate decisions are a lifesaver, especially in times of pandemics such as the situation with COVID-19. In 2023, authors developed a real-time cardiovascular monitoring system for COVID-19 patients, leveraging 5G technology and deep learning techniques [44]. Both theoretical analysis and experimental results indicate that the proposed model effectively addresses relevant issues and enhances the prediction accuracy of cardiovascular diseases to 99.29%.

As well, real-time analysis added significant value in developing IoT medical applications. In 2023, researchers introduced a real-time health monitoring model powered by deep learning and integrated with IoT technology [47]. The proposed model utilizes wearable medical devices to track vital signs and employs various deep-learning techniques to analyze the data. Accordingly, the proposed model is regarded as a useful tool for identifying serious health conditions in athletes, including brain tumors, heart disease, and cancer.

Finally, in the healthcare section, real-time analysis helped in developing hyperglycemia prediction and personalized control recommendations mode. Recently, in 2024, researchers developed an explainable machine-learning model designed to forecast hypoglycemia (<70 mg/dL) and hyperglycemia (>270 mg/dL) up to 60 minutes in advance [48]. The XGBoost machine learning model demonstrated outstanding performance in predicting hypoglycemia, with an area under the receiver operating characteristic curve (AUROC) of 0.998 and an average precision of 0.953. For hyperglycemia, it achieved an AUROC of 0.989 and an average precision of 0.931, surpassing the performance of baseline heuristic and logistic regression models.

Moreover, in social network security, real-time analysis participated in developing a real-time Twitter spam detection and sentiment analysis model in 2022 [40]. The primary goal of the proposed model is to create a system capable of classifying tweets as either 'spam' or 'ham' and assessing their emotional content. The multinomial naïve Bayes classifier reached a classification accuracy of 97.78%, while the deep learning model, specifically an LSTM, achieved a validation accuracy of 98.74% in Twitter spam detection.

Despite the contributions presented by real-time analysis in major sectors such as healthcare and information security, there is still more added value in other fields such as education, where real-time analysis is used to implement the facial emotion recognition model [45]. In 2023, researchers introduced a method utilizing deep learning to assess the real-time engagement of students in online learning by monitoring their facial emotions. This involves examining students' facial expressions to categorize their emotional states during online classes. The system demonstrated accuracy rates of 89.11%, 90.14%, and 92.32% for real-time classification of facial emotions across different datasets.

Moreover, in the education sector, real-time analysis has demonstrated significant assistance in developing a real-time seismic damage prediction model [49]. In 2024, to enhance earthquake early warning (EEW), the researchers proposed a real-time damage prediction framework based on machine learning that forecasts the maximum inter-story drift ratio (MIDR) of structures immediately following the arrival of the P-wave. The proposed framework has been rigorously evaluated through two case studies of seismic damage and a real seismic event, achieving an average accuracy rate of over 96.4% for consistent early-warning risk classification.

Also, in enhancing the agriculture processes, real-time analysis developed a grading fruits visual inspection model [43]. Where in 2022, a study introduced a highly efficient machine vision system that leverages advanced deep learning techniques and stacking ensemble methods to provide a non-destructive and cost-effective solution for automating the visual inspection of fruit freshness and appearance. Real-time testing on actual samples demonstrated an accuracy of 96.7% for apples and 93.8% for bananas, highlighting the effectiveness of the proposed system.

Moving to another major sector which is financial and product manufacturing, real-time analysis has also been used in production lines' potential failure prediction models [41]. In 2021, research introduced a predictive maintenance system designed for manufacturing production lines, aiming to forecast potential failures before they arise. The proposed system employs machine learning techniques to analyze large volumes of real-time sensor data. Real-world testing demonstrated that the system successfully identified production stoppages in advance.

In conclusion, the above models showed a massive contribution in different fields when combining real-time analysis with machine learning techniques. These models demonstrated great results in many domains such as IoT, healthcare, information security, agriculture, finance, software, and many industries. Furthermore, Real-time analysis can generate accurate insights ahead of time so that top managers and decision-makers can take the most optimal action to increase profits, manage risks, control damages, and improve the companies' and institutions' processes.

III. META-LEARNING WITH REAL-TIME ANALYSIS

Recently, there have been a lot of critical situations, business processes, industries, and scenarios where new tasks with minimal datasets occurred, additionally many decision-makers in different fields need immediate insights and instantaneous predictions. But unfortunately, traditional machine-learning models are helpless in such unique cases. Therefore, many researchers started to improve the regular frameworks and implement more powerful machine-learning models based on meta-learning algorithms and with real-time capabilities. Accordingly, in this section, the primary goal is to explain the recent real-time meta-learning models, including showing each model's performance, accuracy, limitations, and future work. Moreover, this demonstration will be categorized based on the used domain such as healthcare, information security, finance and manufacturing.

A. Healthcare

Meta-learning algorithms in the medical domain commonly known as Meta-heath are paramount and crucial as patient lifesaving, especially in case of new diseases with insufficient data to train the traditional machine-learning models, which causes inaccurate insights and predictions. As a result, researchers moved towards meta-learning techniques to build and train their models to gain efficient results. Additionally, in medical processes, time is a matter of life and death which forces doctors and medical staff to act ahead of time to save patients' lives, so real-time analysis combined with meta-learning would build the most appropriate models that can be of great help in the healthcare domain.

A real-time meta-learning model introduced by D Patil et al. (2019) aims to predict health risks for patients being monitored through a smartphone. The model adapts to trends in various physiological signals using a newly developed real-time stream mining algorithm, PARC-Stream. It forecasts health risks dynamically by integrating both historical and real-time risk rules specific to the patient, enhancing the accuracy of predictions. Experimental results demonstrate a high prediction accuracy of 99.04% [52].

A modality translation model proposed by Ali Akbari et al. (2021) enhances the diagnostic capabilities of wearable devices by converting signals from low-power sensors into more interpretable forms that healthcare providers are accustomed to. The model translates Bio-Z into ECG by learning personalized user data without needing multiple independent architectures. Additionally, the model can adjust to new users during testing with minimal samples, thanks to its real-time meta-learning features. Experimental results show a 41% reduction in the percentage root mean square difference (PRD) compared to training a universal model for all users and a 36% reduction compared to training separate models for each user. When adapting to new users, the model outperforms pre-trained models fine-tuned through back-propagation by 40%, even when using as few as two samples during testing [53].

A real-time meta-learning framework for interactive medical image registration, introduced by Z Baum et al. (2022), is designed to integrate registration, interaction, and meta-learning protocols for a clinical application. The framework facilitates the alignment of magnetic resonance (MR) images with interactively acquired, sparsely sampled transrectal ultrasound (TRUS) images. This method achieves a registration error of 4.26 mm, closely matching the best non-interactive 3D-to-3D learning-based approach (3.97 mm) but with significantly less data and in real-time during image acquisition. In contrast, applying sparsely sampled data to non-interactive techniques results in higher errors (6.26 mm), underscoring the effectiveness of interactive MR-TRUS registration, which can be valuable for intraoperative use due to the real-time adaptive process [50].

The ML-NPI model, introduced by T Wang et al. (2023), addresses noncoding RNA-protein interactions (NPI), which play a crucial role in gene regulation, human diseases, and related areas. Despite its significance, computational approaches for large-scale dynamic NPI prediction have received limited attention, particularly in the context of online modeling and real-time prediction. To address this gap, the authors proposed a real-time prediction model that integrates meta-learning with a dynamic ncRNA-protein bipartite graph learning framework to predict NPIs in real time [51].

The YOLO-MR model, proposed by E Lee et al. (2024), aims to enhance early detection and accurate diagnosis of gastrointestinal diseases, with a focus on gastric cancer, ultimately improving patient survival rates. The authors developed this object detection model (YOLO-MR) to efficiently identify cases of cancer, adenoma, and ulcers. By incorporating model-agnostic meta-learning (MAML) for optimal weight adjustments into the YOLO architecture, the model's lesion detection capabilities were significantly enhanced. Experimental results demonstrated an impressive mAP of 96, notably surpassing the conventional YOLO model. The study also examined the effects of data imbalance on accuracy, offering valuable insights into the performance of YOLO-MR with meta-learning and residual blocks, thereby contributing to advancements in real-time lesion detection [54].

B. Information Security

Nowadays, whether in small businesses or large corporations, top managers know the effect of digital attacks on their systems and how much it will cost them if they show any slackness regarding their security-defending systems. Therefore, companies invest a lot of money to build unbreachable security walls that close any found vulnerabilities and instantaneously analyze network traffic data to detect the most known attacks. But unfortunately, due to the massive enhancement of AI techniques besides the growing intelligence of the attackers. Accordingly, hackers and cybercriminals have been able to implement new and much stronger attacks backed up with advanced AI algorithms that current security systems cannot identify. As a result, researchers started to propose machine learning models to enhance the ability of the current security defending systems to detect the new improved attacks and new vulnerabilities, the proposed models are based on meta-learning approaches to train the models on the new unseen tasks and build a real-time infrastructure to instantaneously analyze network traffic and detect digital attacks ahead of time.

A new intelligent framework, proposed by M Snehi et al. (2022), focuses on improving IoT security and Quality of Service (QoS). Given the vast variety and types of IoT devices functioning in smart environments, accurately characterizing network traffic and classifying devices is essential for effective management. To address this, the authors enhanced traffic classification by leveraging the behavioral patterns of IoT network traffic. They introduced a novel IoT classification framework using a Stack-Ensemble approach designed for real-time processing of high-volume IoT traffic. Experimental findings showed an impressive accuracy of 99.94% [55].

A detection model developed by Y Yan et al. (2024) targets cybersecurity risks within the 5G-enabled industrial internet. Given that cyber-attacks like zero-day exploits offer minimal response time for security defenders, protecting industrial control systems from emerging malicious threats becomes increasingly challenging. Traditional supervised intrusion detection models fall short in handling such attacks as they depend heavily on extensive training samples, limiting their effectiveness. To address this, the authors proposed a detection model based on a meta-learning framework designed to enhance both the accuracy and real-time performance of intrusion detection. Experimental results indicate that this model outperforms conventional models in detecting few-shot and zero-shot attacks, making it suitable not only for 5G-enabled industrial internet environments but also adaptable to diverse network settings and attack scenarios [56].

The Meta-Fed-IDS framework, introduced by U Zukaib et al. (2024), addresses security and privacy challenges within the Internet of Medical Things (IoMT), a groundbreaking convergence of medical sensors, devices, and the Internet of Things that is revolutionizing healthcare. The authors presented Meta-Fed-IDS as an advanced framework for detecting cyberattacks in IoMT networks. They emphasized that the framework's real-time architecture is tailored to work effectively across IoMT, fog, and cloud environments. The design leverages an Infrastructure as a Service (IaaS) model on the cloud side and a Software as a Service (SaaS) model on the fog side, ensuring flexibility and adaptability for various network settings [57].

The Meta-RF-GNB (MRG) model, developed by F Rustam et al. (2024), is designed to identify server-based network attacks through an innovative approach that employs advanced AI techniques for real-time threat detection. The researchers introduced the MRG model, which integrates Gaussian Naive Bayes and Random Forest methods for making predictions. This model achieved an impressive accuracy rate of 99%. Its effectiveness was validated through cross-validation, which resulted in a remarkable average accuracy of 99.94% with a very low standard deviation of 0.00002 [58].

C. Finance and Manufacturing

Financial and manufacturing affairs are considered one of the fields where meta-learning models and real-time analysis play a significant role, especially in the factories and stock market, where managers and stockholders want to gain instantaneous accurate insights to make the right decisions. Accordingly, meta-learning can be used with few shots to train models in new unseen tasks, and event-driven architecture can be built to generate predictions in real time.

The SA-NET.V2 model, introduced by M Masouleh (2022), is designed for real-time vehicle detection. The proposed model utilizes deep meta-learning techniques to monitor, locate, and identify various vehicles on an urban scale. The experimental results demonstrate that SA-NET.V2 delivers impressive performance when applied to time-series oblique images captured by unmanned aerial vehicles (UAVs) [62].

The DML model, developed by C Che et al. (2023), focuses on optimizing decision-making for repairing civil aircraft structures. Its aim is to reduce repair costs, enhance repair efficiency, and maintain ongoing aircraft airworthiness. Given the complex operating conditions of civil aircraft, instances where damage exceeds predefined thresholds can make it challenging to derive repair solutions from historical data alone. To address this, the authors proposed a deep meta-learning (DML) model that employs CNN and MAML techniques to extract general features from few-shot, high-dimensional structural health monitoring data, enabling precise repair decisions. Additionally, the model supports continuous classification and decision-making through real-time application and updates of deep meta-learning [61].

Y Zhao et al. (2023) introduced a meta-learning voltage control strategy aimed at enhancing the efficiency of renewable energy use, minimizing large-scale energy losses, and managing voltage deviations during emergency faults in Active Distribution Networks (ADN). This strategy, built on a meta-learning framework, optimizes the output power of various renewable energy inverters to enable swift and effective real-time decision-making with minimal sample data. The results demonstrate that the strategy achieves optimal decisions rapidly, even when faced with emergency faults that have not been previously encountered [63].

The MASSER framework, developed by D Zhan et al. (2024), addresses two key challenges in stock-market analysis: the availability of data and the potential for domain shifts that occur as stock time series evolve. To tackle these issues, the authors introduced the Meta-Adaptive Stock Movement Prediction with Two-Stage Representation Learning (MASSER) framework, which combines self-supervised learning and meta-learning techniques. According to the authors, experiments conducted on two open-source datasets demonstrate that MASSER improves average accuracy by 5% to 9.5% compared to leading state-of-the-art methods [59].

The IPMP approach, introduced by L F Braghirolli et al. (2024), addresses damage control and risk mitigation by enhancing production and maintenance planning in digital manufacturing systems. The authors developed the Integrated Production and Maintenance Planning (IPMP) approach, which incorporates dynamic simulation-based optimization and meta-learning for failure prediction. This method selects the most effective prognostic technique for real-time machine failure forecasting. Experimental results indicate that this approach reduces lead time by 20.9% and tardy jobs by 25.9% compared to systems using static dispatching rules and single-method prognostics [60].

To enhance energy efficiency and reduce computational load in safety-critical robotic systems, C O'Hara et al. (2024) introduced a real-time meta-learning framework designed to dynamically allocate system resources and prevent shutdowns or stalls. Their comprehensive evaluation showed that this framework decreased average energy consumption by 13.71% and CPU utilization by 29.07% compared to 'always-on' configurations, all while maintaining system performance and safety [64].

In the context of the growing renewable energy sector and advancing energy storage technology, H Shen et al. (2024) identified that stochastic scheduling of microgrids can lead to higher operational costs and increased resource waste. To address these issues and enhance resource utilization efficiency, they proposed a real-time meta-learning model for microgrid scheduling. The experimental findings demonstrate that this model effectively improves energy utilization and reduces operational costs during the initial stages of microgrid operation [65].

IV. Open Challenges and Future Work

Despite the significant progress made in meta-learning for real-time analysis, several issues and open challenges in various fields such as healthcare, information security, finance, and manufacturing still require further investigation.

A. Healthcare

Recently, researchers have applied popular AI techniques to develop meta-learning models for real-time analysis, including the YOLO (You Only Look Once) object detection algorithm. By incorporating model-agnostic meta-learning (MAML) into YOLO, there has been a notable enhancement in the detection of lesions. Exploring the potential of these methods in other domains and for rare diseases, where training datasets may be limited, could be beneficial [54].

In another area, recent studies in mobile health surveillance have shown that advanced models can effectively predict health risks for patients monitored via smartphones. These models use both historical data and dynamic risk rules tailored to individual patients to improve risk prediction accuracy. However, further advancements are needed to develop healthcare systems that are specific to various diseases and patient needs [52].

B. Information Security

Meta-learning models with real-time capabilities offer significant benefits for combating cyber-attacks, protecting systems against prevalent vulnerabilities, and reducing cybersecurity risks, particularly within 5G-enabled industrial networks. Given the rapid response required to address zero-day attacks, which complicates the protection of industrial control systems from novel malicious threats, the authors have proposed advanced detection models to enhance both accuracy and real-time performance of intrusion detection systems. Nevertheless, there is still potential for improving the detection accuracy and efficiency of current models by experimenting with different optimization parameters to boost their effectiveness [56].

Additionally, preemptively detecting cyberattacks using meta-learning models is essential for securing the Internet of Medical Things (IoMT). However, there is a need for further enhancements, such as broadening the dataset, improving data balancing strategies, and exploring additional optimization algorithms to increase the applicability of recent methods in Multi-IoT-Environment networks. Further testing is also necessary for network surveillance and vulnerability detection across various domains [57].

Although meta-learning models in real-time analysis have shown promise in improving IoT security and Quality of Service (QoS), integrating big-data tools like Apache Spark and examining their effectiveness against sophisticated cyber-attacks could lead to the development of autonomous defense solutions [55].

Recent research has also provided valuable insights into detecting server-based network attacks through advanced AI methods designed for real-time detection. Despite its importance, challenges such as dataset availability and scalability persist. Greater efforts are needed to enhance dataset scalability for large-scale applications and to explore the adaptability of these methods across different server platforms and operating systems [58].

C. Finance and Manufacturing

In the renewable energy sector, particularly in optimizing energy storage technology, there is significant potential to explore the integration of various Reinforcement Learning (RL) and meta-learning techniques for microgrid optimization. As the field evolves, more sophisticated algorithms can be developed to enhance the adaptability, efficiency, and robustness of microgrid systems. Continued research in this area could lead to more intelligent and autonomous energy management solutions, which are essential for the sustainable and reliable operation of microgrids in the future [65].

Additionally, with rising energy demand and ongoing advancements in renewable energy technology, active distribution networks (ADN) have become increasingly crucial. However, the integration of substantial amounts of renewable energy has made ADN structures more complex and vulnerable, often leading to emergency faults. Effective voltage control during such events is critical. While some strategies offer rapid adaptation, they generally focus only on the distribution network and overlook physical factors such as information transmission delays and inverter placement. Future research should aim to develop voltage control methods that incorporate these physical considerations [63].

In the realm of digital manufacturing systems, meta-learning-based failure prediction is vital for minimizing risks by enhancing production and maintenance planning and selecting the most effective prognostic method for real-time machine failure prediction. However, limitations related to data availability persist, presenting opportunities for future research. Potential areas for exploration include integrating manufacturing quality issues with machine degradation monitoring and addressing human workforce constraints. Investigating alternative optimization techniques, such as Reinforcement Learning, could also improve current methods [60].

In stock-market analysis, researchers have focused on real-time meta-learning models to address challenges such as data scarcity and potential domain shifts in stock time series. While existing models for stock movement prediction provide valuable insights for investors, there is still room for improvement. Future work could benefit from exploring graph neural networks and enhancing robustness against noisy data [59].

V. CONCLUSION

The research started with highlighting the definition, objectives, methodologies, categories, and recent models of meta-learning and real-time analysis as distinct concepts. After that, the research explored the significance of integrating meta-learning with real-time capabilities by presenting recent meta-learning real-time models and highlighting the added value across various domains. The research also addressed the limitations, open challenges, and future directions associated with these emerging models.

The primary goal of the research is to focus on the rapidly evolving field of meta-learning with its applications in real-time analysis and to show the significant values added when combining real-time analysis with meta-learning techniques, especially in certain use cases where decision-makers need immediate accurate insights when dealing with new unseen tasks with few-shot data to train their models.

In addition, the key methodologies, algorithms, and frameworks driving advances in this area have been explored and highlighted in many successful applications across various domains such as healthcare, finance, IoT, and information security, where real-time analysis is critical. Furthermore, the integration of meta-learning techniques has shown promise in addressing the limitations of traditional machine-learning models, particularly in terms of generalization and quick adaptation to new tasks.

Overall, this study underscores the importance of continued research and development in the field of meta-learning for real-time analysis. As the landscape of real-time data continues to expand, the need for robust, adaptive, and efficient learning models becomes increasingly critical. The advancements in meta-learning not only enhance the performance of real-time systems but also open new avenues for innovative applications in various sectors.

References

[1] Habeeb, Riyaz Ahamed Ariyaluran, Fariza Nasaruddin, Abdullah Gani, Ibrahim Abaker Targio Hashem, Ejaz Ahmed, and Muhammad Imran. "Real-time big data processing for anomaly detection: A survey." International Journal of Information Management, volume 45, 2019, pp. 289-307.

[2] Kitchin, Rob. "The real-time city? Big data and smart urbanism." GeoJournal, volume 79, 2014, pp. 1-14.

[3] Schiemer, Martin, Lei Fang, Simon Dobson, and Juan Ye. "Online continual learning for human activity recognition." Pervasive and Mobile Computing, volume 93, 2023, doi: 10.1016/j.pmcj.2023.101817.

[4] Kreps, Jay, Neha Narkhede, and Jun Rao. "Kafka: A distributed messaging system for log processing." In Proceedings of the NetDB, vol. 11, no. 2011, pp. 1-7. 2011.

[5] Carbone, Paris, Asterios Katsifodimos, Stephan Ewen, Volker Markl, Seif Haridi, and Kostas Tzoumas. "Apache flink: Stream and batch processing in a single engine." The Bulletin of the Technical Committee on Data Engineering 38, no. 4 (2015), pp. 28-38.

[6] Zheludkov, Michael, and Timur Isachenko. "High Performance in-memory computing with Apache Ignite." Lulu. com, 2017.

[7] Stan, Cristiana-Stefania, Adrian-Eduard Pandelica, Vlad-Andrei Zamfir, Roxana-Gabriela Stan, and Catalin Negru. "Apache spark and apache ignite performance analysis." In 2019 22nd international conference on control systems and computer science (CSCS), pp. 726-733. IEEE, 2019.

[8] Singh, Amarjeet, Vinay Singh, Alok Aggarwal, and Shalini Aggarwal. "Event Driven Architecture for Message Streaming data driven Microservices systems residing in distributed version control system." In 2022 International Conference on Innovations in Science and Technology for Sustainable Development (ICISTSD), pp. 308-312. IEEE, 2022.

[9] Guerra, Jorge Luis, Carlos Catania, and Eduardo Veas. "Datasets are not enough: Challenges in labeling network traffic." Computers & Security, volume 120, 2022, pp. 102810.

[10] A. Vettoruzzo, M. -R. Bouguelia, J. Vanschoren, T. Rögnvaldsson and K. Santosh, "Advances and Challenges in Meta-Learning: A Technical Review," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 46, no. 7, pp. 4763-4779, July 2024, doi: 10.1109/TPAMI.2024.3357847.

[11] Vanschoren, Joaquin. "Meta-learning: A survey." arXiv preprint arXiv:1810.03548 (2018).

[12] T. Hospedales, A. Antoniou, P. Micaelli and A. Storkey, "Meta-Learning in Neural Networks: A Survey," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 9, pp. 5149-5169, 1 Sept. 2022, doi: 10.1109/TPAMI.2021.3079209.

[13] Finn, Chelsea, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks." In International conference on machine learning, pp. 1126-1135. PMLR, 2017.

[14] Baik, Sungyong, Myungsub Choi, Janghoon Choi, Heewon Kim, and Kyoung Mu Lee. "Meta-learning with adaptive hyperparameters." Advances in neural information processing systems, volume 33, 2020, pp. 20755-20765.

[15] Li, Da, Yongxin Yang, Yi-Zhe Song, and Timothy Hospedales. "Learning to generalize: Meta-learning for domain generalization." In Proceedings of the AAAI conference on artificial intelligence, vol. 32, no. 1. 2018.

[16] Gharoun, Hassan, Fereshteh Momenifar, Fang Chen, and Amir Gandomi. "Meta-learning approaches for few-shot learning: A survey of recent advances." ACM Computing Surveys, ACM Computing Surveys, Volume 56, Issue 12, Article No.: 294, pp. 1 – 41, doi: 10.1145/3659943 2023.

[17] Rothfuss, Jonas, Christopher Koenig, Alisa Rupenyan, and Andreas Krause. "Meta-learning priors for safe bayesian optimization." In Conference on Robot Learning, pp. 237-265. PMLR, 2023.

[18] Choe, Sang, Sanket Vaibhav Mehta, Hwijeen Ahn, Willie Neiswanger, Pengtao Xie, Emma Strubell, and Eric Xing. "Making scalable meta learning practical." Advances in neural information processing systems, volume 36, 2024, pp. 1-20.

[19] Tian, Yingjie, Xiaoxi Zhao, and Wei Huang. "Meta-learning approaches for learning-to-learn in deep learning: A survey." Neurocomputing, volume 494, 2022, pp. 203-223.

[20] Santoro, Adam, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. "Meta-learning with memory-augmented neural networks." In International conference on machine learning, pp. 1842-1850. PMLR, 2016.

[21] Zhao, Yuyang, Zhun Zhong, Fengxiang Yang, Zhiming Luo, Yaojin Lin, Shaozi Li, and Nicu Sebe. "Learning to generalize unseen domains via memory-based multi-source meta-learning for person re-identification." In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 6277-6286. 2021.

[22] Wang, Jane X., Zeb Kurth-Nelson, Dhruva Tirumala, Hubert Soyer, Joel Z. Leibo, Remi Munos, Charles Blundell, Dharshan Kumaran, and Matt Botvinick. "Learning to reinforcement learn." arXiv preprint arXiv:1611.05763, 2016, pp. 1-17.

[23] Nam, Taewook, Shao-Hua Sun, Karl Pertsch, Sung Ju Hwang, and Joseph J. Lim. "Skill-based meta-reinforcement learning." arXiv preprint arXiv:2204.11828, 2022, pp. 1-22.

[24] Rusu, Andrei A., Dushyant Rao, Jakub Sygnowski, Oriol Vinyals, Razvan Pascanu, Simon Osindero, and Raia Hadsell. "Meta-learning with latent embedding optimization." arXiv preprint arXiv:1807.05960, 2018, pp. 1-17.

[25] Wang, Jiaxing, Jiaxiang Wu, Haoli Bai, and Jian Cheng. "M-nas: Meta neural architecture search." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 04, pp. 6186-6193. 2020.

[26] Nichol, Alex, Joshua Achiam, and John Schulman. "On first-order meta-learning algorithms." arXiv preprint arXiv:1803.02999, 2018, pp. 1-15.

[27] Nichol, Alex, and John Schulman. "Reptile: a scalable metalearning algorithm." arXiv preprint arXiv:1803.02999, volume 2, 2018, pp. 1-3.

[28] Li, Huaiyu, Weiming Dong, Xing Mei, Chongyang Ma, Feiyue Huang, and Bao-Gang Hu. "LGM-Net: Learning to generate matching networks for few-shot learning." In International conference on machine learning, pp. 3825-3834. PMLR, 2019.

[29] Snell, Jake, Kevin Swersky, and Richard Zemel. "Prototypical networks for few-shot learning." Advances in neural information processing systems, volume 30, 2017, pp. 1-11.

[30] Koch, Gregory, Richard Zemel, and Ruslan Salakhutdinov. "Siamese neural networks for one-shot image recognition." In ICML deep learning workshop, vol. 2, no. 1, pp. 1-30. 2015.

[31] Ravi, Sachin, and Hugo Larochelle. "Optimization as a model for few-shot learning." In International conference on learning representations. 2016, pp. 1-11.

[32] Li, Zhenguo, Fengwei Zhou, Fei Chen, and Hang Li. "Meta-sgd: Learning to learn quickly for few-shot learning." arXiv preprint arXiv:1707.09835 (2017), pp. 1-11.

[33] Graves, Alex, Greg Wayne, and Ivo Danihelka. "Neural turing machines." arXiv preprint arXiv:1410.5401, 2014, pp. 1-26.

[34] Mishra, Nikhil, Mostafa Rohaninejad, Xi Chen, and Pieter Abbeel. "A simple neural attentive meta-learner." arXiv preprint arXiv:1707.03141, 2017, pp.1-17.

[35] Stonebraker, M., Çetintemel, U., and Zdonik, S. "The 8 requirements of real-time stream processing." ACM SIGMOD Record, vol. 34, no. 4, pp. 42-47, Dec. 2005.

[36] Means, Barbara, Yuki Toyama, Robert Murphy, Marianne Bakia, and Karla Jones. "Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies." repository.alt.ac.uk, (2009), pp. 1-93.

[37] J. Chen and X. Ran, "Deep Learning With Edge Computing: A Review," in Proceedings of the IEEE, vol. 107, no. 8, pp. 1655-1674, Aug. 2019, doi: 10.1109/JPROC.2019.2921977.

[38] Meng, Xiangrui, Joseph Bradley, Burak Yavuz, Evan Sparks, Shivaram Venkataraman, Davies Liu, Jeremy Freeman et al. "Mllib: Machine learning in apache spark." Journal of Machine Learning Research 17, no. 34 (2016): 1-7.

[39] Chakraborty, Mainak, and Ajit Pratap Kundan. "Grafana." In Monitoring cloud-native applications: Lead agile operations confidently using open source software, pp. 187-240. Berkeley, CA: Apress, 2021.

[40] Rodrigues, Anisha P., Roshan Fernandes, Adarsh Shetty, Atul K, Kuruva Lakshmanna, and R. Mahammad Shafi. "[Retracted] Real-Time Twitter Spam Detection and Sentiment Analysis using Machine Learning and Deep Learning Techniques." Computational Intelligence and Neuroscience, 2023, pp. 1-14.

[41] Ayvaz, Serkan, and Koray Alpay. "Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time." Expert Systems with Applications, Volume 173, 1 July 2021, 114598

[42] Zhang, Le, Zhichen Wang, Lei Wang, Zhe Zhang, Xu Chen, and Lin Meng. "Machine learning-based real-time visible fatigue crack growth detection." Digital Communications and Networks, Volume 7, 2021, pp. 551-558.

[43] Ismail, Nazrul, and Owais A. Malik. "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques." Information Processing in Agriculture, Volume 9, 2022, pp. 24-37.

[44] Tan, Liang, Keping Yu, Ali Kashif Bashir, Xiaofan Cheng, Fangpeng Ming, Liang Zhao, and Xiaokang Zhou. "Toward real-time and efficient cardiovascular monitoring for COVID-19 patients by 5G-enabled wearable medical devices: a deep learning approach." Neural Computing and Applications, 2023, pp. 1-14.

[45] Gupta, Swadha, Parteek Kumar, and Raj Kumar Tekchandani. "Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models." Multimedia Tools and Applications, Volume 82, 2023, pp. 11365-11394.

[46] Mujahid, Abdullah, Mazhar Javed Awan, Awais Yasin, Mazin Abed Mohammed, Robertas Damaševičius, Rytis Maskeliūnas, and Karrar Hameed Abdulkareem. "Real-time hand gesture recognition based on deep learning YOLOv3 model." Applied Sciences, Volume 11, 2021, pp.1-15.

[47] Wu, Xingdong, Chao Liu, Lijun Wang, and Muhammad Bilal. "Internet of things-enabled real-time health monitoring system using deep learning." Neural Computing and Applications, 2023, pp. 1-12.

[48] Duckworth, Christopher, Matthew J. Guy, Anitha Kumaran, Aisling Ann O'Kane, Amid Ayobi, Adriane Chapman, Paul Marshall, and Michael Boniface. "Explainable machine learning for real-time hypoglycemia and hyperglycemia prediction and personalized control recommendations." Journal of Diabetes Science and Technology, Volume 18, 2024, pp. 113-123.

[49] Zhang, Hui, Dinghao Yu, Gang Li, and Zhiqian Dong. "A real-time seismic damage prediction framework based on machine learning for earthquake early warning." Earthquake Engineering & Structural Dynamics, Volume 53, 2024, pp. 593-621.

[50] Z. M. C. Baum, Y. Hu and D. C. Barratt, "Meta-Learning Initializations for Interactive Medical Image Registration," in IEEE Transactions on Medical Imaging, vol. 42, no. 3, pp. 823-833, March 2023, doi: 10.1109/TMI.2022.3218147.

[51] Tao Wang, Wentao Wang, Xin Jiang, Jiaxing Mao, Linlin Zhuo, Mingzhe Liu, Xiangzheng Fu, and Xiaojun Yao, "ML-NPI: Predicting Interactions between Noncoding RNA and Protein Based on Meta-Learning in a Large-Scale Dynamic Graph," in Journal of Chemical Information and Modeling, vol. 64 (7), 2024, pp. 2912-2920, DOI: 10.1021/acs.jcim.3c01238.

[52] Patil, Dipti Durgesh, and Vijay M. Wadhai. "Real-time meta learning approach for mobile healthcare." In Smart Innovations in Communication and Computational Sciences: Proceedings of ICSICCS-2018, pp. 11-23. Springer Singapore, 2019.

[53] Akbari, Ali, Jonathan Martinez, and Roozbeh Jafari. "A meta-learning approach for fast personalization of modality translation models in wearable physiological sensing." IEEE journal of biomedical and health informatics 26, no. 4 (2021): 1516-1527.

[54] E. Lee, J. -S. Kim, D. K. Park and T. Whangbo, "YOLO-MR: Meta-Learning-Based Lesion Detection Algorithm for Resolving Data Imbalance," in IEEE Access, vol. 12, pp. 49762-49771, 2024, doi: 10.1109/ACCESS.2024.3384088.

[55] Snehi, Manish, and Abhinav Bhandari. "A novel distributed stack ensembled meta-learning-based optimized classification framework for real-time prolific IoT traffic streams." Arabian Journal for Science and Engineering, vol. 47, 2022, pp. 9907-9930.

[56] Yan, Yu, Yu Yang, Fang Shen, Minna Gao, and Yuheng Gu. "Meta learning-based few-shot intrusion detection for 5G-enabled industrial internet." Complex & Intelligent Systems, vol. 10, 2024, pp. 4589-4608.

[57] Zukaib, Umer, Xiaohui Cui, Chengliang Zheng, Dong Liang, and Salah Ud Din. "Meta-Fed IDS: Meta-Learning and Federated Learning Based Fog-Cloud Approach to Detect Known and Zero-Day Cyber Attacks in IoMT Networks." Journal of Parallel and Distributed Computing, Volume 192, October 2024, pp. 104934.

[58] F. Rustam, A. Raza, M. Qasim, S. K. Posa and A. D. Jurcut, "A Novel Approach for Real-Time Server-Based Attack Detection Using Meta-Learning," in IEEE Access, vol. 12, pp. 39614-39627, 2024, doi: 10.1109/ACCESS.2024.3375878.

[59] Zhan, Donglin, Yusheng Dai, Yiwei Dong, Jinghai He, Zhenyi Wang, and James Anderson. "Meta-adaptive stock movement prediction with two-stage representation learning." In Proceedings of the 2024 SIAM International Conference on Data Mining (SDM), pp. 508-516. Society for Industrial and Applied Mathematics, 2024.

[60] Braghirolli, Lynceo Falavigna, Lúcio Galvão Mendes, Hendrik Engbers, Simon Leohold, Yuri Triska, Maurício Randolfo Flores, Raphael Odebrecht de Souza, Michael Freitag, and Enzo Morosini Frazzon. "Improving production and maintenance planning with meta-learning-based failure prediction." Journal of Manufacturing Systems, vol. 75, 2024, pp. 42-55.

[61] Che, Changchang, Huawei Wang, Xiaomei Ni, and Minglan Xiong. "Few-shot structural repair decision of civil aircraft based on deep meta-learning." Engineering Applications of Artificial Intelligence, vol. 125, 2023, pp. 106695.

[62] Khoshboresh-Masouleh, Mehdi, and Reza Shah-Hosseini. "SA-NET. V2: Real-time vehicle detection from oblique UAV images with use of uncertainty estimation in deep meta-learning." arXiv preprint arXiv:2208.04190 (2022).

[63] Zhao, Yincheng, Guozhou Zhang, Weihao Hu, Qi Huang, Zhe Chen, and Frede Blaabjerg. "Meta-learning based voltage control strategy for emergency faults of active distribution networks." Applied Energy, vol. 349, 2023, pp. 121399.

[64] O'Hara, Christopher Aaron, and Takehisa Yairi. "Graph-based meta-learning for context-aware sensor management in nonlinear safety-critical environments." Advanced Robotics, vol. 38, no. 6 (2024), pp. 368-385.

[65] Shen, Huan, Xingfa Shen, and Yiming Chen. "Real-Time Microgrid Energy Scheduling Using Meta-Reinforcement Learning." Energies, vol. 17, no. 10 (2024), pp. 2367.

[66] P. C. Latane, P. A. Dhakate, V. S. Ubale and D. S. Mantri, "Real-time Data Visualization for the IOT Application using Tableau Platform," 2024 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2024, pp. 1-5, doi: 10.1109/ESCI59607.2024.10497376.

[67] Parmezan, Antonio Rafael Sabino, Huei Diana Lee, and Feng Chung Wu. "Metalearning for choosing feature selection algorithms in data mining: Proposal of a new framework." Expert Systems with Applications, volume 75, 2017, pp. 1-24.