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Smart Health Monitoring System of Agricultural Machines: Deep Learning-based Optimization with IoT and AI

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Abstract. Implementing intelligent monitoring systems for Agricultural Machinery (AM) is hindered by the intricate and costly nature of the Internet of Things (IoT) sensor technologies. The heavy reliance on cloud and fog computing, the availability of network infrastructure, and the need for expert knowledge pose challenges in rural areas that lack network connectivity. Using edge devices, such as smartphones, which possess significant computational capabilities, is a potential solution that has not yet been fully realized in the commercial sphere. Furthermore, the increasing demand from users for economically viable and user-friendly technology serves as a driving force for transitioning away from expensive and intricate sensors towards more cost-effective alternatives. In the IoT era, there is anticipated to be a widespread network connection between a vast array of AM and service centers. Using smartphone applications has increased the potential for edge computation on smartphones to significantly aid in network traffic control. The development of an Artificial Intelligence (AI) - -based data analytic method poses a significant challenge due to the need to optimize for the limited computational capabilities of smartphones. However, the users' demand for affordable technology renders it resistant to easy penetration. This paper uses IoT and AI to propose a Smart Health Monitoring System for Agricultural Machines with Deep Learning-based Optimization (SHMAM-DLO). This paper aims to propose a Fusion Genetic Algorithm (FGA) methodology and Artificial Neural Network (ANN) for optimization during monitoring the health of AM. The proposed approach enables cost-effective utilization of smartphone end devices by leveraging their built-in microphones instead of relying on expensive IoT sensors.

1 Introduction

Throughout history, agriculture has played a pivotal role in the development of human civilization by serving as a fundamental source of sustenance, essential raw materials, and a means of livelihood for a significant proportion of the world's population. In the current epoch, characterized by a persistent rise in global agricultural requirements to sustain and nourish an ever-growing populace, a pressing imperative exists for developing and

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implementing inventive and environmentally sound farming methodologies [1]. At the core of this endeavor lies the incorporation of state-of-the-art technology to enhance agriculture's efficiency, productivity, and ecological sustainability. The agricultural sector has undergone a significant transformation due to the emergence of the IoT and AI. This technological advancement has provided farmers with intelligent tools and data-driven insights, enabling them to optimize their operations effectively.

The utilization of AM equipped with highly efficient instruments significantly impacts various aspects of the agricultural industry, including farming practices, pricing dynamics, supply chain management, and the delivery of food products [2]. AI-based systems in the SHMAM of AM hold significant importance for industries, as they strive to implement economically viable and dependable systems successfully. This would enable widespread accessibility to such systems for users. Previous studies have investigated the predictive aspects of SHMAM for motorized rotating machinery [3]. These studies employed a manually structured Artificial Neural Network (ANN) with manually defined hyperparameters to evaluate signals from multiple sensors, including vibration, pressure, temperature, etc. As the IoT continues to expand rapidly, various industries are progressing towards adopting advanced data analysis techniques for real-time monitoring and maintenance prediction.

The motivation for this research stems from the limitations of the current technology for SHMAM of AM systems in effectively mitigating sudden failures. The primary factors contributing to the challenging installation of these systems on older machines are the reliance on costly sensors, the need for Cloud/Fog computation, the requirement of network availability, the necessity of expert knowledge, the complexity of the code system, and the utilization of inbuilt hardware-based technologies [4]. Moreover, the decision to abstain from utilizing edge devices is influenced by the intricate nature of sensor technology and the incompatibility of such devices with outdated machinery. This, in turn, significantly impacts the procedures associated with asset management and leads to an undesirable increase in expenses. Integrating IoT devices with AI technologies presents a viable solution, albeit with two notable limitations. Firstly, the cost associated with this integration renders it an expensive endeavor. Installing these IoT devices onto existing machinery can be burdensome and complex. Microphones serve as the most cost-effective sensors to substitute and minimize the use of expensive sensors [5] to establish an efficient AI-driven edge-enabled SHMAM system.

AM, encompassing a wide range of equipment such as tractors and combine harvesters, is the fundamental mechanical infrastructure of contemporary farming practices. Utilizing these machines is crucial for planting, cultivating, and harvesting crops, enabling a level of scale and efficiency that was previously inconceivable [6]. Unforeseen downtime or failure in a vital component of AM can have substantial ramifications during a critical operation. The potential consequences of compromised crop yields, wastage of valuable resources, and the overall undermining of farming practices may pose significant challenges to the sustainability of agricultural systems.

Conventional maintenance approaches frequently encompass predetermined examinations and regular servicing, which may not consistently align with optimal timing or cost efficiency. The emergence of the IoT has brought about the possibility of implementing real-time monitoring and forecasting within the AM domain. By integrating sensors and IoT connectivity into these machines, farmers can monitor their equipment's condition and operational efficiency remotely [7]. This capability allows farmers to proactively identify potential problems, strategically plan maintenance activities, and prevent expensive equipment failures during crucial agricultural tasks.

Moreover, AI and DL methodologies have exhibited remarkable proficiency in data analytics, pattern identification, and modeling predictions [8]. When implemented in the context of the extensive data produced by IoT sensors on AM, these technologies have the potential to offer significant insights for enhancing maintenance practices, enhancing operational efficiency, and guaranteeing the durability of the AM. The main aim of this study is to create and execute a Smart Health Monitoring System for Agricultural Machines that utilizes DLO, IoT, and AI to observe the state, efficiency, and maintenance needs of AM.

2 Literature Survey

Smart Agriculture was born from the IoT and AI transforming the agricultural industry. The need for food production to feed a growing population has made advanced technologies essential. This survey reviews IoT and AI-driven smart health monitoring systems for AM research on methodologies, implementations, output, benefits, and challenges. This survey provides valuable insight into the current situation and highlights the opportunity to improve current agricultural methods' effectiveness, sustainability, and adaptability to the changing agricultural landscape.

Royal et al. (2023) use IoT technology and machine learning algorithms to optimize their smart irrigation system. They use IoT sensors to collect environmental data and machine learning algorithms to improve irrigation schedules [9]. This demonstration shows sensor deployment in various fields and cloud-based analytics. The results show improved water use, crop efficiency, and resource conservation. The benefits come from sustainability and resource conservation. However, sensor maintenance and data connectivity in remote areas may be difficult.

Gupta et al. (2022) propose using genetic algorithms to drive evolutionary machine learning. This system is designed for IoT-based agricultural vehicle health monitoring [10]. Researchers optimize vehicle health monitoring systems using evolutionary algorithms. The implementation includes real-time data collection from agricultural vehicle IoT sensors and anomaly detection using genetic algorithms. Early fault detection and proactive maintenance strategies reduce downtime and maintenance costs. The benefits include machine durability and reduced operational costs, but algorithm complexity and data scalability may be issues.

Maduranga and Abeysekera (2020) analyze machine learning applications in IoT-based agriculture and smart farming. Instead of presenting a methodology, the paper surveys agricultural Internet of Things (IoT) machine-learning techniques [18]. The result is a thorough understanding of machine learning applications in agriculture, which can inform future implementations. Knowledge dissemination and application insights are the main benefits of this approach. However, the lack of implementation details may limit it.

The authors Li et al. (2021) extensively examine machine learning-driven big data analytics in IoT-enabled smart healthcare systems [12]. The researchers survey healthcare IoT machine learning applications. The output includes machine learning methods and healthcare implementations. A vast knowledge base is a benefit of healthcare IoT. However, the research does not focus on agriculture, which may limit its applicability to agricultural IoT projects.

In their study, Dhanya et al. (2022) examine deep learning-based computer vision methods for intelligent agriculture. Agriculture images and data are analyzed using deep learning models [13]. The implementation uses computer vision algorithms in various agricultural fields. The result is better agriculture and disease detection. A key benefit of this method is its accurate and detailed image analysis. This method requires large labeled datasets and computational resources, which are drawbacks.

Shaikh et al. (2022) examine machine learning and AI in precision agriculture and smart farming [14]. Current and future applications are examined in the methodology. The theoretical framework includes precision agriculture principles and concepts. This study sheds light on agricultural AI applications. This study lacks details on AI implementation in agriculture, which is a limitation. Gupta et al. (2020) propose using economic data analytics and AI on IoT edge devices to monitor AM health [15]. The method uses AI to analyze edge device data. The proposed system uses AI models on IoT edge devices to monitor real-time health. The health monitoring system is cost-effective. One benefit of this method is cost-effectiveness. However, edge device limitations may present challenges.

In their recent publication, Gupta and Gupta (2022) proposed an optimal lightweight AI end device for agriculture vehicle health monitoring [16]. This study aims to create a lightweight AI system for vehicle health monitoring. This study shows how agricultural vehicles can use AI-enabled devices. The vehicle health monitoring system improves. One benefit of lightweight design is reducing device weight. However, lightweight devices' processing limitations may cause drawbacks. This literature review covers Smart Agriculture's vast knowledge and advances, focusing on the "Smart Health Monitoring System for AM" that uses IoT, AI, and Distributed Ledger Technology [17]. This technology's potential to transform agriculture is highlighted by the literature review's thorough examination of its methodologies, implementations, and results [11].

3 Smart Health Monitoring System of Agricultural Machines with Deep Learning-based Optimization (SHMAM-DLO)

The SHMAM-DLO is a comprehensive technological system developed to facilitate continuous monitoring and effective control of AM's health, functionality, and operational effectiveness in real time. This system utilizes sophisticated technologies, such as the IoT, AI, and DL-based optimization, to optimize the performance of farming machinery, such as tractors, harvesters, and irrigation systems.

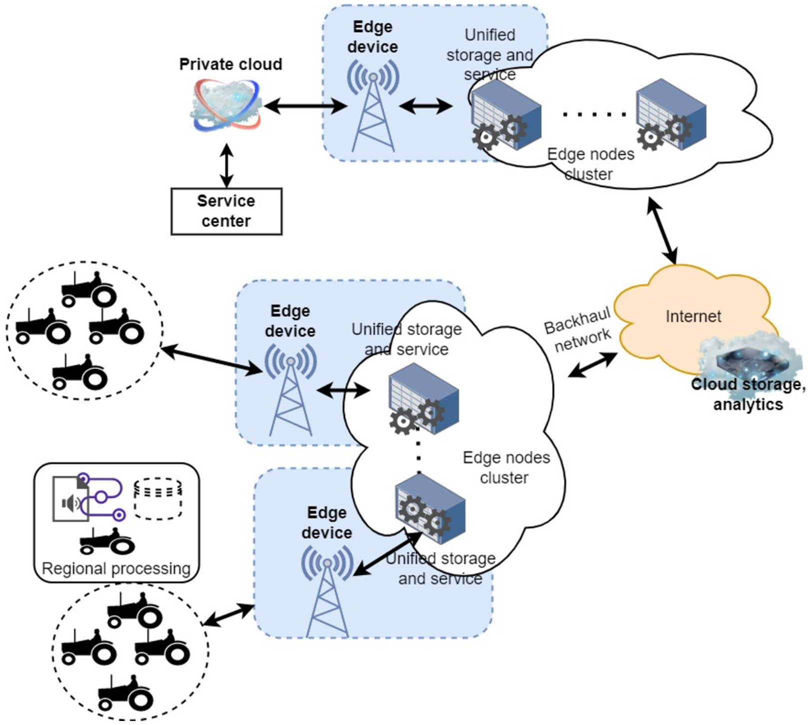

Fig. 1. Smartphone-based edge computation architecture for SHMAM

Fig. 1 shows the smartphone-based Edge Computation (SEC) architecture for SHMAM. As depicted in Fig. 1, it can be inferred that the development within this proposed framework may encounter challenges arising from the requirement to transmit large amounts of unprocessed information in real-time. This is particularly evident when considering the substantial quantity and diverse range of AMs connected to a singular Edge node. The concurrent transmission of information from many AMs through various pools of edge nodes can lead to bottlenecks and subsequent latency issues on the Backhaul network, particularly when service centers are located at a considerable distance from the fields where the users operate. The exploration of the edge computing paradigm encompasses the advancement of real-time applications on linked end devices, representing a significant area of research. This focus holds the potential to address prominent challenges, including reducing data size within the network, thereby mitigating the associated transmission bandwidth costs.

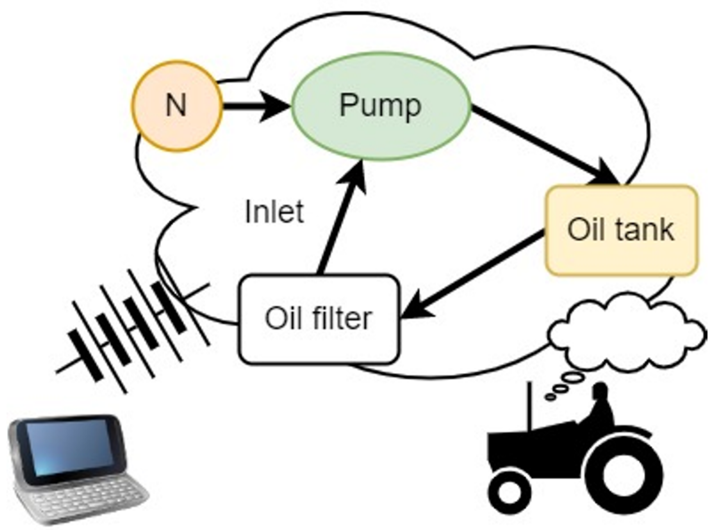

Fig. 2. Smart Health monitoring system for oil filter

Fig. 2 depicts the Smart Health monitoring system for oil filters. The current SHMAM's reliance on pricey sensors and complex technologies discourages customers from investing in cutting-edge technology. Thus, in the existing SEC design, as seen in Fig. 2, a sound-based inspection of AM is the answer to lower the structure's expenditure. Layered computing has been suggested at edge devices to use smartphone characteristics for the SHMAM system, hence increasing the system's capability. It has been driven to provide an ergonomically optimized intelligent analytics (IA) solution to facilitate the successful use of finer computation. Drones and other AMs may also be integrated with an ergonomically optimized IA tool. Integrated Bluetooth Microphones (BM) close to sound-generating elements can capture sounds from those parts. Such microphones are simple to link with a smartphone. Conversely, users may capture the created sound by positioning their smartphone's microphone next to it.

Prominent agricultural corporations are now advancing automated tractors, including various technologies such as machine sync systems, AutoTrack vision, and the AutoTrac row sensing system, among others. These systems provide remote farm equipment operation, enhancing the user's effectiveness and precision. The current state of self-driving agricultural machinery necessitates human supervision for performance monitoring and troubleshooting of the numerous associated equipment. The latest developments in the In-build display tutorial have the potential to reduce downtime and enhance efficiency in large-scale agricultural operations. The integration of an AI-based SHMAM system has the potential to be a groundbreaking technique for enhancing the service experience of users.

The inexpensive AI system built in this study may be integrated into the production process, allowing for the transmission of warnings using different Wi-Fi technologies across the network. One potential approach to mitigating AM is using smartphone applications, which can assist users in detecting and preventing AM by analyzing the auditory signals emitted by nearby wearable electronics. The acoustic data emanating from an AM within the agricultural setting provides valuable insights into the present condition of the machine's subsystems. This enables the prompt and efficient implementation of preventative maintenance measures. The primary focus of this study is to emphasize the use of ML techniques in creating a robust and efficient sound-responsive SHMAM system. This system is specifically designed to operate on edge computing gadgets, offering a heightened detection level and a reduced occurrence of false alarms. Ultimately, implementing these techniques aims to enhance the overall quality of service the SHMAM system provides. This research aims to design a shallow ANN with reduced computational complexity for the SHMAM system, tailored explicitly for smartphone implementation. The technique comprises many vital steps:

Step 1: A recording device is installed in the vicinity of the oil pump filter of the AM pneumatic system.

Step 2: The recordings have been obtained using six distinct filters that exhibit varying degrees of defective condition.

Step 3: Three-minute soundtracks were produced for each filter, designated from 1 to 5. In this context, 1 represents a regular running filter, whereas 5 indicates a choked filter. These refer to five Fault Levels (FL) of oil filters in AM.

Step 4: Features are derived from the unprocessed audio recordings.

Step 5: The FGA is employed to choose the minimal necessary features that align with the inputs to the ANN and the number of neurons in the hidden layers.

Step 6: The Scaled Conjugate Gradient Backpropagation (SCGBP) technique is employed to train and evaluate the ANN to construct the model for categorization.

Step 7: The optimal option is chosen for implementing a smartphone application or on-board diagnostic system as an edge processor.

The process for developing an inexpensive AI model for deployment on a smartphone is presented in Fig. 3. The network may process computed information in two ways by utilizing IT-based Edge device technology. There are two primary aspects to consider: firstly, the prioritization of data transmission during a crisis or essential diagnostic situations, and secondly, the flow of information during regular operating conditions. The resulting analysis might be submitted to an information repository rather than a large volume of audio data in the latter scenario. In this scenario, the system does not identify faults, and Original Machinery Manufacturers (OMMs) often do not express interest in it. Conversely, the scenario mentioned above is of utmost significance and holds substantial relevance for OMM in its pursuit of enhancing its properties. The first transmission of alarm or problem detection data can be directed toward service centers or OMM facilities inside the network. Once a reliable network connection is established, these centers can retain the information in the phone's memory and communicate it to the server. OMM may further employ this data to enhance their product's quality.

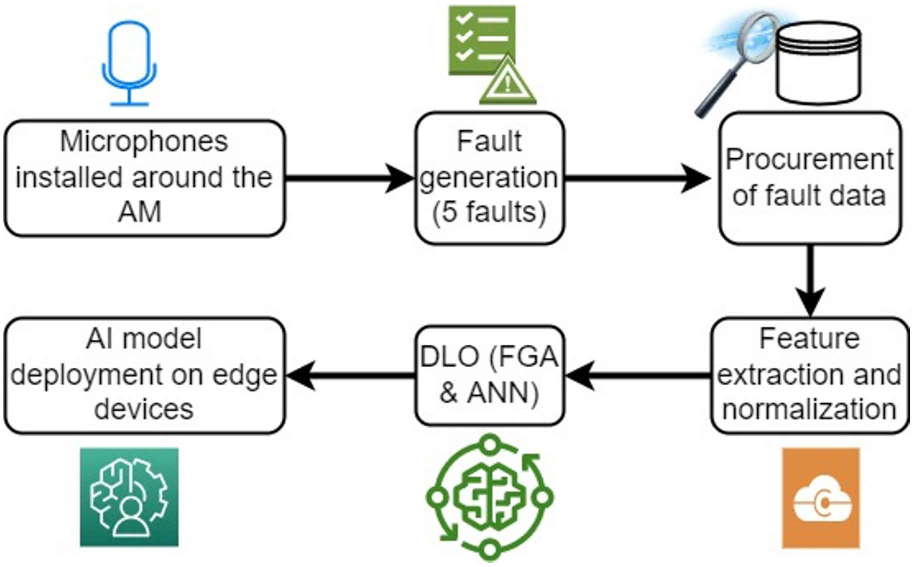

Fig. 3. Framework for Smart Health Monitoring System of Agricultural Machines with Deep Learning-based Optimization

Within the service center, after receiving a critical alert and assessing the state of the relevant component, a proficient operator can communicate with the tenant of the designated AM for more details. Suppose the occupier is unable to make contact. In that case, the service provider will assess the repair needs for the diagnostic issue and dispatch an expert to perform maintenance on the component promptly. The approach presented has broad applicability, as it may be employed for the SHMAM of all components inside AM processes. The utilization of OBDs or smartphone applications, facilitated by BM located close to all surveillance components, is intended to operate according to the approach shown in Fig. 3.

3.1 DLO with FGA and ANN

During the training process of an ANN, the numerical values assigned to the inputs are frequently expressed using a binary number system. Each input feature is considered eligible for training by the ANN if its value is 1, else it is rejected by the Genetic Algorithm (GA). Furthermore, the weights and bias are represented as actual numbers in the chosen ANN architecture. The traditional optimization approach, which involves simultaneously manipulating all variables, demonstrates limitations when used to ANNs with many mixed variables, mainly when the number of hidden neurons is an integer value.

Algorithm 1. DLO with FGA and ANN

Input:
Input Data: X (Feature matrix), Output Data: y (Target variable), Population Size: pop_size, Maximum Generations: max_gen, Crossover Probability: crossover_prob, Mutation Probability: mutation_prob, Number of Hidden Neurons (Level I): hidden_neurons_level I
Output:
Optimal ANN Structure: optimal_structure (Number of hidden neurons, selected features) Trained ANN Weights and Bias: trained_weights_bias
Initialization:
Generate an initial population of chromosomes for Level I optimization representing different ANN structures.
Bi-Level Optimization Loop:
1. Level I Optimization (Structure Optimization):
Encode each chromosome to represent the ANN structure, including the number of hidden neurons and selected features.
Apply HGA to optimize the ANN structure based on the mean square error μ of the trained network in Level II.
Chromosome Encoding (Level I):
chromosome={binary_representation_selected_features,hidden_neurons}
Fitness Function (Level I):fitness=1/μ
2. Level II Optimization (Training):
Train the ANN using the optimized structure from Level I.
Extract the mean square error μ as the fitness value for Level I optimization.
3. Check Stopping Criteria:
If the maximum number of generations (max_gen) is reached or convergence criteria are met, exit the loop.
Post-Processing:
1. Extract Optimal ANN Structure:
Extract the best chromosome from the final population based on fitness in Level I.
Decode the chromosome to obtain the optimal ANN structure, including the number of hidden neurons and selected features.
Chromosome Decoding (LevelI):selected_features=decode(binary_representation_selected_features)
2. Extract Trained ANN Weights and Bias:
Train the ANN with the optimal structure obtained in Level I.
Extract the trained weights and bias from the trained ANN.

Algorithm 1 shows the DLO with FGA and ANN. The DLO paradigm is exemplified in the SHMAM, wherein the result of each level serves as input for the subsequent level. Within this theoretical framework, at Level I, FGA undertakes the optimization of the ANN structure. This optimization is achieved by utilizing the output obtained from the ANN training process at Level II, represented by the trained network's Mean Square Error (MSE). Combining higher-level FGA with the lower-level ANN training process results in an ideal solution. This approach presents an alternate methodology for addressing the challenges of developing lightweight ANNs. The proposed technique's goal functions at levels I and II consist of diverse choice factors.

4 Results and discussion

The entirety of the simulation has been executed using MATLAB 2019b. For the level-II analysis, the ANN toolbox in MATLAB is employed. This toolbox utilizes the SCGBP-trained ANN approach coupled with the batch training mode. It is worth noting that the batch training mode is considerably quicker and yields fewer errors compared to incremental training. As the training of the ANN approaches its ideal performance, the size of the gradient will converge towards a much-diminished value. The training of the ANN is halted when the error value hits a threshold of less than or equal to $1x10^{-5}$.

In contrast, the validation check refers to the consecutive iterations during which the validation performance does not exhibit any improvement. In the ANN training technique, the termination criterion is defined as a value of 5, indicating that the training process will cease once this criterion is met. To train the level-II ANN structure, the complete feature dataset, comprising five audio segments, is initially normalized within the range of -1 to 1. Subsequently, the dataset is randomly rearranged to create three distinct subsets: training, validation, and test data. These subsets are allocated proportions of 65%, 20%, and 15% of the total dataset.

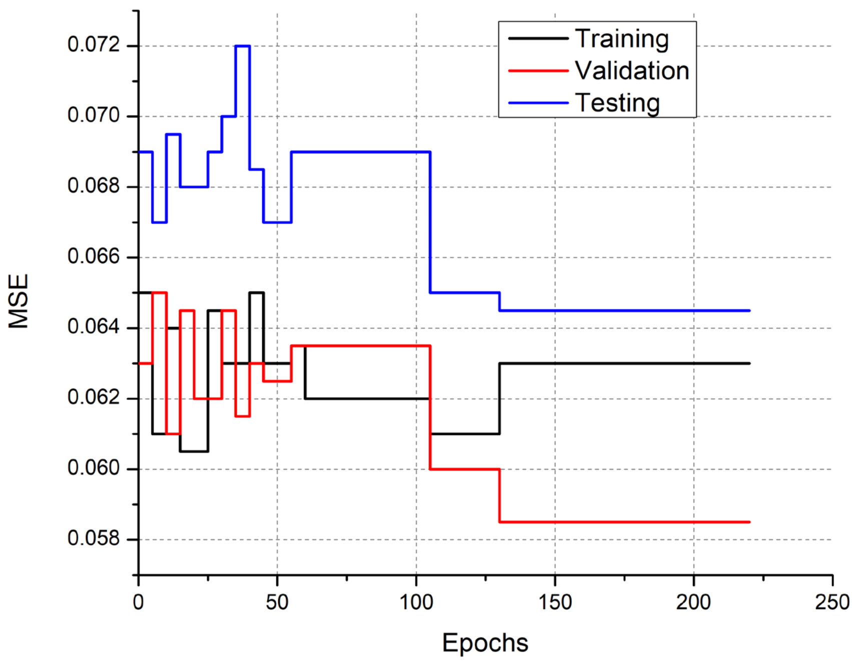

Fig. 4. MSE convergence curve for DLO with ANN and FGA

Fig. 4 illustrates the convergence curve of the MSE for the DLO technique utilizing ANN and FGA. The presented table demonstrates a negative correlation between the MSE and the number of epochs observed across the training, validation, and testing datasets. This observation suggests that the model is acquiring knowledge and enhancing its performance as time progresses. Nevertheless, it can be observed that the convergence rate exhibits a decline after approximately 150 epochs, indicating that the model is approaching its maximum performance level. The MSE values of the training dataset are the lowest among the three MSE values, suggesting that the model exhibits a strong ability to represent the training data accurately. The MSE for the validation set exhibits a slight increase compared to the MSE for the training set, albeit remaining relatively low. This observation suggests that the model exhibits strong generalization capabilities when applied to data that it has not been previously exposed to. The MSE for the testing data exhibits the highest value among the three MSE values, albeit relatively low. This finding suggests that the model demonstrates strong performance on data not exposed to during the training phase. In general, the table presented demonstrates that the DLO model with ANN and FGA can acquire knowledge and enhance its performance progressively. Furthermore, the model demonstrates a commendable ability to extrapolate its acquired knowledge to previously unseen data.

Nevertheless, it can be observed that the convergence rate exhibits a decline after approximately 150 epochs, thereby indicating that the model is approaching its maximum performance level.

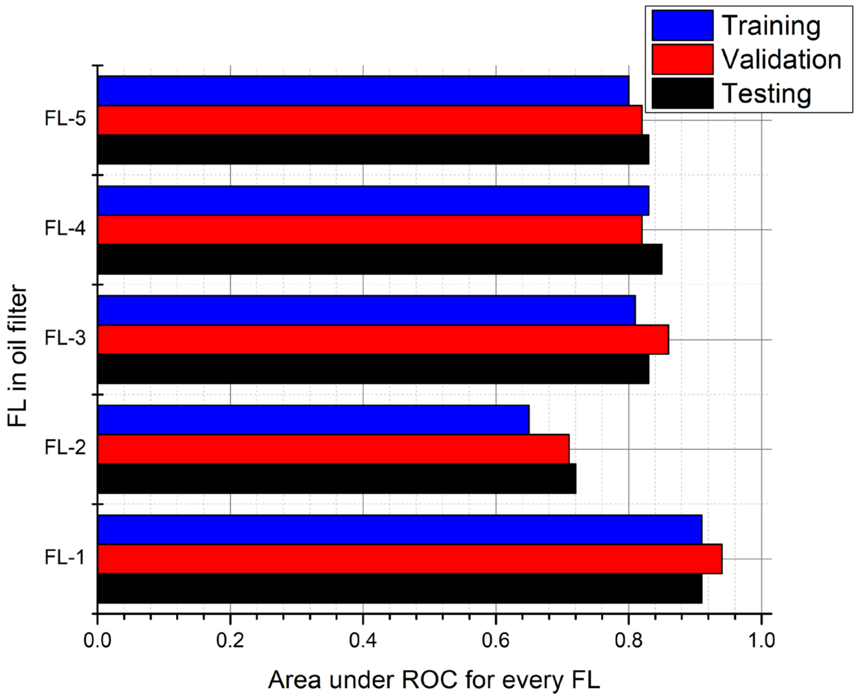

Fig. 5. Area under ROC (AUC) for detecting FL using the proposed SHMAM-DLO framework

Fig. 5 shows the Area under ROC (AUC) for detecting FL using the proposed SHMAM-DLO. The Area Under the Curve (AUC), representing each class, for evaluating the training, validation, and testing datasets are presented in Fig. 5. In this analysis, it is evident that the mean AUC values for all FLs in the discrimination of learned samples (trained data) is 0.8. This finding serves as an indication of the efficacy of the trained model. In a similar vein, the mean value of the AUC for all FLs in the validation and testing datasets is 0.83 and 0.828, respectively. The AUC assessment criteria demonstrate that the proposed model can perform significantly on average. Therefore, employing just microphones for health monitoring of AMs is feasible.

5 Conclusion

The present study employs the integration of IoT and AI to propose a Smart Health Monitoring System for Agricultural Machines with a focus on Deep Learning-based Optimization (SHMAM-DLO). This study aims to provide a methodology called FGA in conjunction with ANN to optimize the monitoring of AM health. The suggested methodology facilitates the efficient exploitation of smartphone end devices by capitalizing on their included microphones, thereby reducing the reliance on costly IoT sensors. This ANN is designed exclusively for the SHMAM system, focusing on its smartphone application. The AUC, which represents the performance of each class, is offered as a metric for evaluating the training, validation, and testing datasets. This investigation demonstrates that the average

AUC value for all FLs in the classification of learned samples (trained data) is 0.8. This discovery provides evidence of the effectiveness of the trained model. The average value of the AUC for all FLs in the validation and testing datasets is 0.83 and 0.828, respectively. The assessment criteria for the AUC reveal that the suggested model has a notable capability to achieve a high level of performance on average. Hence, utilizing microphones rather than costly sensors for the health monitoring of AMs in the suggested SHMAM-DLO system is viable.

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