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A Machine Learning Approach on Data-Driven Thermal Monitoring of Induction Motors in Electrified Powertrains

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Abstract: - The research is aimed to determine a data-driven approach towards the thermal monitoring of Induction Motors in the context of electrified powertrains. We apply the examination of the temperature data with the help of the appropriate set of sensors, including Thermocouples, Resistance Temperature Detectors , as well as Infrared sensors in combination with the mixture of the Machine Learning algorithms to predict the service requirements and operational needs of the examined system . The data, provided by the thermal sensors, makes it possible to predict the demand for the maintenance of the part or optimize the work of the coolant pumps. Thus, we conduct the performance analysis of several ML models, including Artificial Neural Networks , Support Vector Machines , Decision Trees , and Random Forests across the range of different epochs of the training. Our analysis has shown that ML-based approaches can be highly efficient in accurately predicting the forthcoming maintenance requirements using the sensor-based information. Precisely, the most efficient was the ANN model, producing the result of 97.65%. It was followed by SVM and DT, producing the results of 94.5% and 92.3%, respectively. Finally, RF was only able to produce the result of 90.25%, falling behind the other approaches. Our comparison has provided multiple implications to the relative strengths and weaknesses of the employed models, and the choice of whether they are appropriate must be conducted through the prism of these comparisons. In addition, the analysis of the performance across different epochs has shown that the subsequent ones have produced the better results, which makes the training process crucial.

Keywords: thermal monitoring, induction motors, electrified powertrains, predictive maintenance, machine learning

I. INTRODUCTION

One of the central technologies in the sphere of sustainable transportation, electric powertrains have been developed as a cleaner and more resource-efficient answer to traditional internal combustion engines .[1]–[3] As the industry embraces this new approach, it is crucial for the operation of electric powertrains to be both reliable and efficient . One of the focal aspects of this operation is thermal management of induction motors, often referred to as the heart of electric propulsion systems.

An induction motor is an essential part of numerous types of electromechanical systems, converting electrical energy into mechanical energy and thus propelling vehicles at impressive efficiency rates . The performance of these devices is not flawless, however, as induction motors produce heat during operation [4]–[6]. Without an effective system of thermal management, they are at risk of overheating, resulting in performance degradation . Thus, thermal monitoring methodologies that could identify temperature changes in the device and adjust operation to prevent overheating are of critical importance in this setting.

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The objective of this paper is to investigate a data-driven concept of thermal monitoring of a single induction motor in electrified powertrains. The developed method will be designed with the support of high-capacity sensors and up-to-date algorithms of machine learning. Aiming at the prediction of the necessity to perform maintenance and the optimization of the operation of the coolant pump, the plans will be based on the real-time data on the temperature of the device collected by the sensors installed within the motor. The major goal of the paper is to investigate the purpose of the thermal monitoring of induction motors in electrified powertrains and the perspectives of machine learning introduction in predictive maintenance and operational optimization [7]–[9].

The appearance of electrified powertrains has obviously influenced the automotive industry, as it presented a new, greener variant of operating vehicles. Electrified or electric powertrains are comprised mainly of electric motors, batteries, and associated power electronics, all of which generate a certain degree of heat in the process of their work. Therefore, efficient thermal management of the components is paramount for the reliability and longevity of electric powertrains [10]–[12]. Historically, thermal management problems have been an area of extensive research and development activities with respect to electrified powertrains. Early electric vehicles often had issues with overheating, as an inadequate amount of heat dissipation ultimately resulted in battery and motor degradation. Subsequent efforts have focused on mitigating the effect and inventing novel techniques that would allow for more efficient thermal management [6], [13], [14].

Since induction motors represent the part of electric powertrains that facilitates the conversion of electrical energy into mechanical energy and contributes to the operation of vehicles, avoiding an efficient thermal management of those is inadvisable. Namely, the process of their functioning results in a proportional amount of heat emitted, an accumulation of which may lead to catastrophic thermal stress. As a consequence, efficient thermal monitoring techniques must be incorporated in order to timely detect variation in temperature and respond by emitting coolant and reducing the temperature differnetial in the whole operation of the motor. By doing so, the possibility of overheating and, consequently, the risk of a motor failure is mitigated, and the performance and lifespan of the motor are increased. Moreover, the technology employed actually permits an even more efficient long-term maintenance, as the repairs can be done preventatively, as the temperature is constantly monitored [15]–[17]. A variety of sensor technology is capable of measuring the temperature variations and response times of induction motors. These include, but are not limited to, thermocouples, Resistance Temperature Detectors , and Infrared sensors [18]–[20].

Thermocouples operate due to the well-known Seebeck effect. When there is a temperature difference between two dissimilar metals, the voltage produced is proportional to the temperature gradient. RTDs depend on the known variation of electrical resistance in relation to temperature, and therefore, thermocouples and RTDs are accurate and stable. In contrast, IR sensors depend on measuring the infrared emitted by a body to get the temperature. Therefore, on one hand, thermocouples or RTDs are used due to their high accuracy, while on the other hand, IR sensors are used because of the fact that the temperature might be at a location that is either hard or impossible for a person to reach. In either case, the advantages, and disadvantages should be considered, and then the best choice should be made [21]–[23].

For temperature measurement, the accurate devices are the thermocouples and RTDs, which are contact devices measuring directly the temperature. Still, IR sensors are designed to measure the temperature without physically contacting the object. Machines require sensors to measure their temperature, and for high measurement accuracy, it is impossible to decide whether to use thermocouples or RTDs. A lot of motors do not allow for physical contact required to make accurate temperature readings. Either decision should involve the use of IR sensors, which may be largely affected by factors such as ambient temperatures and surface properties. The other device does not directly measure the temperature because it is contact. The existing temperature change techniques are largely accurate.

II. METHODOLOGY

IIn the world of electrified powertrains, the integration of multiple sensors, such as Thermocouples, RTDs and Infrared sensors is a key breakthrough in efficient thermal management for induction motors. Displaced in different areas within the motor, the sensors form a network which captures the subtle differences in temperature absolutely essential for preemptive maintenance and optimal performance. The flow of data starts as the sensors monitor the temperature change and relay the information in real-time to the central controller system.

The crux of the system lies in the controller's ability to interpret this data in the context of preset limits. Should the temperature values exceed the limits that have been set in the system's memory, an alarm is raised, signifying the need for predictive maintenance. At this point, coolant deployment becomes essential in counteracting the motor from overheating. The coolant circulates within the loop creating the required cool stream. All this data is at the disposal of so-called predictive analytics. All these data are first collected and stored in datasets where they are further examined and used to train Machine Learning models whose main purpose it to predict the need for maintenance and the optimal coolant pump operation. Since, almost every computer science assignment help service tries to use the subject-knowledge, or a specific field-knowledge, machine learning is the discipline of utmost importance in today's computer science and data science ecosystem. The work flow of the proposed systema re shown in figure 1.

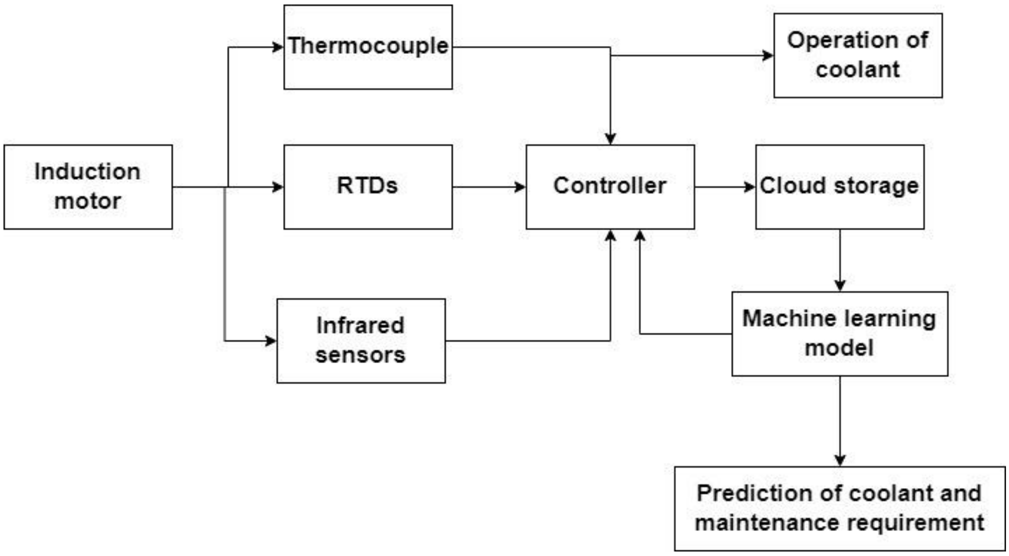

Figure. 1. Workflow of the proposed system

There are numerous algorithms that can be used in Machine Learning in order to make sure the motor operates as effectively as possible. ANNs use a complex system of nodes in multiple layers that resembles a human brain to recognize subtle patterns and correlations. With their ability to disperse the data in high-dimensional space and map them to hyperplanes, SVMs are extremely effective in classification and regression. RF and DT are also brilliant; they can combine numerous models into one which is far better at predicting the motor's condition. In essence, this research project aims to revolutionize electric powertrain management through the integration of cutting-edge sensor technologies, control, and machine learning algorithms. By establishing connections between data collection, predictive analytics, and proactive maintenance, our work challenges the fundamental boundaries of efficiency and reliability in electrified transportation systems. In this innovative era, the possibilities of unhindered traffic operation for electric vehicles are becoming increasingly realistic.

A. Sensors used in this research

In the complex ecosystem of thermal monitoring for induction motors particularly in an electrified powertrain, sensors play a vital role. Among a large variety of sensors, specifically for application in the described system, Thermocouples, RTDs, and IR sensors are useful. Each of them has a different operation scheme. Thermocouples work, according to the Seebeck effect, in a way that any temperature gradient between two dissimilar metals results in a proportional voltage. This voltage is to be amplified and conditioned before its further transmission to the main controller of the system . However, RTDs depend on the naturally occurring changes in the resistance of the sensor element with the alternations of the temperature indicating exact values. RTDs utilize similar signal conditioning circuits to convert the resistance alternations to the voltage signal for the transmission to the main controller. Similarly, IR sensors are used to measure temperature without direct contact, as with the above-mentioned sensors. These sensors are acquiring infrared radiation from any object and transforming it into the electrical signal using photodetectors.

After the sensors made the measurement of temperature in an area of an object instead of the temperature measurement of the output, the data should be received by the main controller. In the past, this was mainly done via wired connections, so involved problems with entrapped or irregularly moveable parts . At the moment, traditionally, mostly wireless communication means are used like Wi-Fi, Bluetooth, or Zigbee. The sensors' readings are transmitted to the central part of the system at once, allowing to use any of them almost instantly in the monitoring system. However, the data will be useless without further storage and use in a cloud. The ability to store temperature data elsewhere than a central physical device and analyze it with applying machine learning algorithms is a valuable advantage. It can be done with several cloud computing solutions like AWS, Azure, or Google Cloud.

B. Preprocessing of the dataset

For the purpose of induction motor thermal monitoring experimentation in laboratory settings, the deployment of IoT sensors is a significant innovation in data collection and analysis. As IoT sensors capture the changes in motor temperature, the data undergoes the first step known as data preprocessing, involving the implementation of a dedicated pipeline for further utilization in training of Machine Learning models. The dataset pertaining to this case includes 2800 readings detected by the sensors; thus, preprocessing is initiated to provide for the successful training of models.

The first technique in the data preprocessing pipeline is cleaning and inspection of data, majorly aimed at detection and elimination of outliers. Outlying data may serve to distort the findings of data analysis or pollute the relevant and sufficient input of the models, necessitating the deletion of erroneous data and the outliers present. Thus, the evaluation of mean and standard deviations of the dataset is conducted, and outliers detected are removed, while the missing data is completed, imputed, or interpolated for sufficient preservation of its entirety.

The next technique implemented in data preprocessing is the extraction and selection of features or their analysis from the initial, comprehensive dataset. Since the acquired data with the help of sensors is multidimensional, the usage of all features will result in excessive dimensionality of the preprocessing of models, hence impeding the work efficiency of said models. Several methods have been adopted to this effect, such as PCA or pairwise correlation analysis to detect and analyze the most echoing patterns of spikes and other features in models, contributing significantly to the dataset and the completion of machine learning tasks.

Following the feature selection process, the dataset still undergoes either normalization or standardization to facilitate its usage. Normalization entails the conversion of features to the comparable range, while the standardization of the dataset centers its layout around a specified mean, with a standard deviation of one. These two methods enable the minimization of the massive effects of different scales of the data features or its power, providing greater efficiency, robustness, and convergence levels in the models. Additional to that, the dataset is divided into training and exploratory sets, with the present case implementing a prescribed 70/30% ratio, respectively.IPassing through the temporal segmentation, the dataset is further sundered into different training epochs for the model. In the meantime, cross-validation techniques such as k-fold validation are implemented to ensure that the model, train it, and evaluate its success and overall completion of the envisioned task on in-training epochs, retaining efficiency across the board. The iterative training of models employing different types of machine learning , including Decision Trees , Support Vector Machines , Random Forests , or Artificial Neural Networks , makes it possible for them to learn the patterns and relationships in the sensor and preprocessed data. As a result, proper methods for operation or predictive maintenance of induction motor thermal monitoring are determined.

III. MACHINE LEARNING MODELS

Artificial Neural Networks represent a significant cornerstone of the ML toolkit in this research paradigm. Built in resemblance to the human brain neural architecture, artificial neural networks are made up by interconnected nodes organized in layers. Leveraging forward and backward propogation, ANNs learn to detect complex patterns and relationships present within the preprocessed sensor data. Having the capability to model non-linear relationships and adjust to versatile datasets, ANNs represent a powerful force in predictive maintenance and operation optimization tasks related to the induction motor thermal monitoring application . By utilizing artificial neural networks, the researchers intend to unlock hidden patterns and consequently actionale intelligence behind the vast amounts of data, helping to drive the efficiency and reliability of the electric powertrain. .The inability to model non-linear relationships present within the data, as well as the tendency to produce high variance and low bias models can be attributed as the predominant disadvantage behind the model, rendering it far from perfect serving as an ultimate model for each occasion.

Support Vector Machines represent another major player ML model under this research paradigm. Renowned for its ilk's versatility and robustness, support vector machines are highly used in classification and regression tasks. Utilizing forward and bckward propogation, the SVM learns to place the hyperplanes in corresponding positions, gradually separating classes or fitting the data in terms of regression . Through the power of kernel trick and hyperparameter tuning, SVMs serve their purpose in relation to the inherently difficult and unpredictable induction motor thermal monitoring application, providing a robust tool for data driven decision making and mantainence strategies. Random Forests and Decision Trees represent the ensemble learning techniques utilized in the realm of this research application. Through the wisdom of the crowd, multiple decision tree models help in alleviating overfitting and increasing of model robustnes. Using Bagging and Boosting Strategies in separating of the vast data into more manageable chunks, each decision tree member of the forest model refers to learning informative value of features as it gradually travels down the hierarchy.

IV. RESULT AND DISCUSSION

As a result of rigorous testing and training of the models, it became evident that the strongest model in terms of prediction was the Artificial Neural Network (ANN) model. Specifically, the ANN model demonstrated remarkable accuracy of 97.65%. The strength of the model was that it determined complex patterns in the sensor data while maintaining testing precision and accuracy. In such a way, the ANN model predicted the maintenance needs and the most beneficial operation strategy for induction motor thermal monitoring.

Secondly, the results show that the Support Vector Machine model was the second-best choice for the specified case. Specifically, the model had a suitable accuracy level of 94.5%. The reason for the model's popularity was the ability to work effectively in high-dimensional spaces and form the most optimal dividing lines for datasets. As a result, the model predicted sensor data effectively and with the highest precision.

The third-best model was the Decision Trees model. The accuracy of the model was 92.3%. The model worked by splitting the dataset into two or more sets using simple decision dates. Quick and mass splitting defined the informative nature of the process for sensor data. As a result, the model showed 92.3 % accuracy in analyzing the runtime efforts and predicting intervention of alarms. Finally, the Random Forest model was the weakest model in the present set. The model demonstrated accuracy of 90.25 %. The prediction was close to other models but lower than an acceptable level for the present case. The random forest combined multiple decision trees to predict the most general outcomes. The accuracy of each model are show in figure 2.

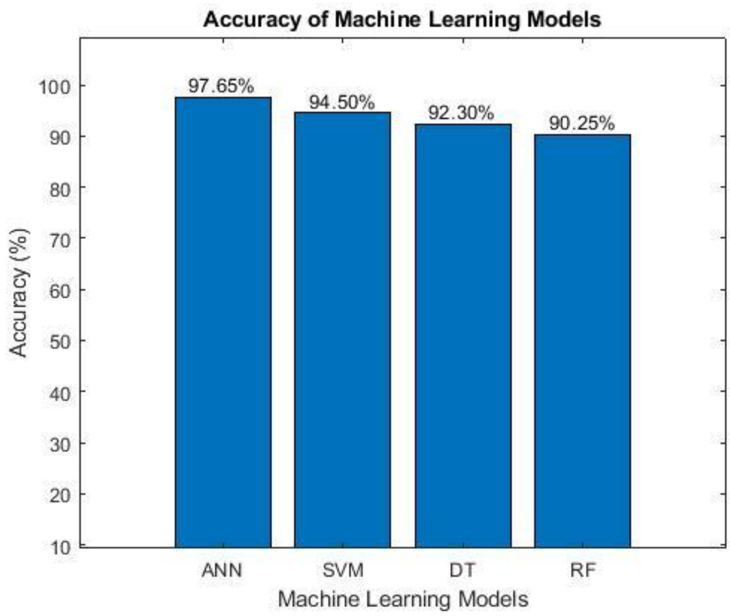

Figure 2. Accuracy of each model

The figure 3 represents the values of performance metrics, such as precision, recall, F1 score, and accuracy, for each Machine Learning model used in the context of the discussed research. Precision is the proportion of true positives of all instances that were classified as positive, while recall is the proportion of true positives of all positive instances. The F1 score is the harmonic mean of precision and recall, providing a balance for the overall diagnostic of the model. Finally, accuracy estimates how correct a model is on the overall. The table represents that Artificial Neural Network is the best model according to each metric, having over 97% precision, recall, F1 score, and accuracy. Thus, the discussed ML model can explore the complexity of the data generated by sensors and areas within the motor and, therefore, have high accuarcy in prediction maintenance and operation optimization.

Support Vector Machine , is closing the gap between the current model to ANN, with 98.68% and 94.55% of precision and recall, accordingly. It is followed by Decision Tree and Random Forest models that also have a rather good performance, though the scores are a little over 90% in each case.

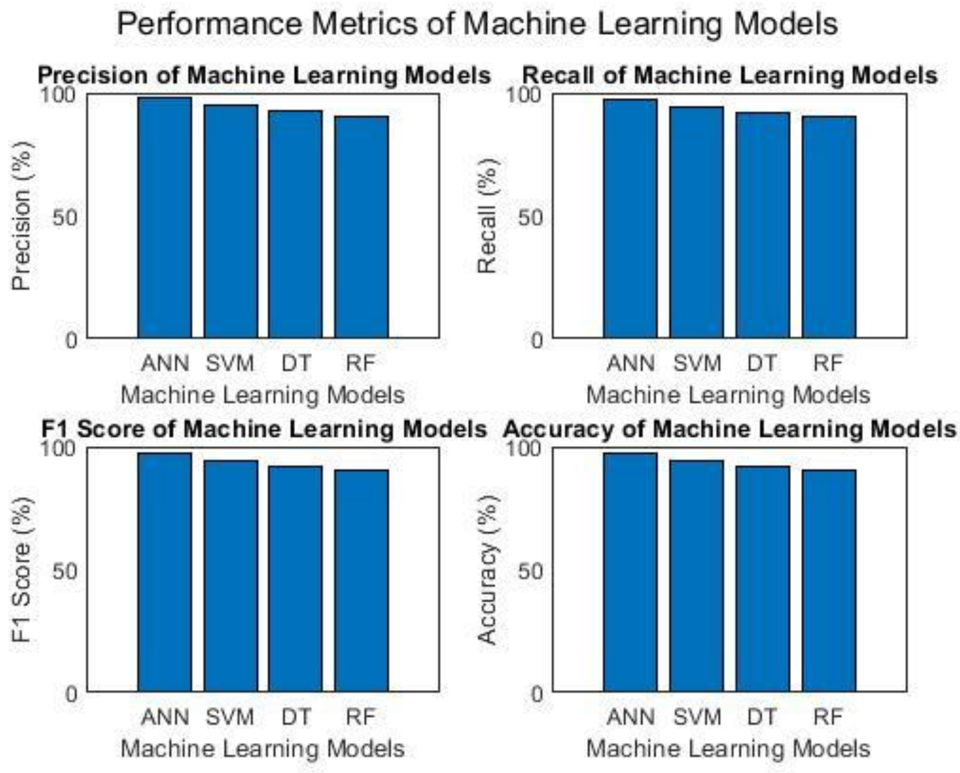

Figure 3. Performance score of each model

Confusion matrices provide a full-scale overview of the classification performance of each Machine Learning model, making it clear through the matrices whether an ML model can predict the status of induction motor health properly based on this sensor data each time as shown in figure 4. In confusion matrices, the actual classes are arranged in rows (negative class for normal operation, positive class for maintenance needs) and the predicted classes by ML models are present in the columns. Looking at the Artificial Neural Network model's confusion matrix, there appears to be a high number of true positives and true negatives , which means that normal operation and maintenance needs are well-classified each time . Since the numbers of false positives and false negatives are small, as well, the level of accuracy of the ANN is satisfactory.

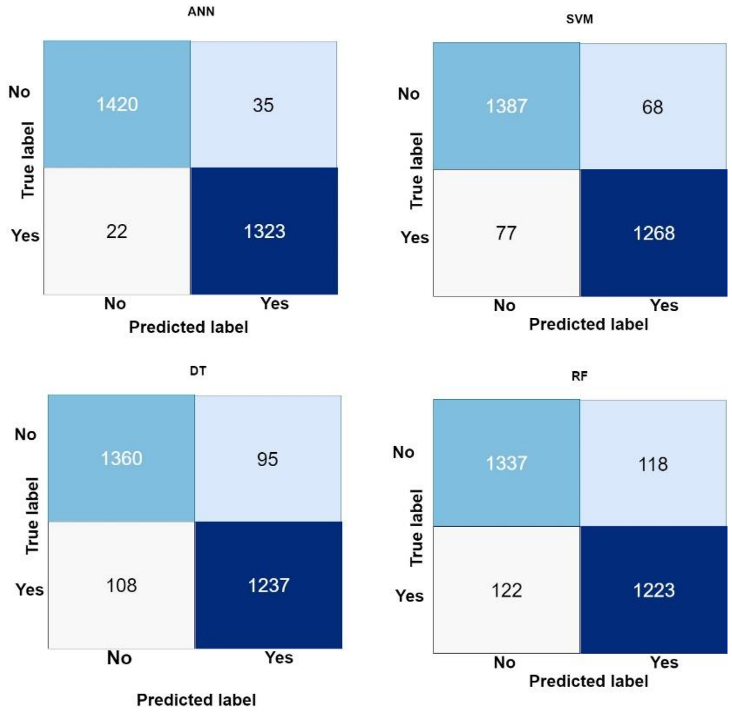

Figure 4 Performance score of each model

The Support Vector Machine model seems to show a similar performance, except for the fact that the number of false positives and false negatives is a little higher in this model than in the ANN model. Regardless of this difference and the fact that the ANN model is stronger in accuracy in general, the levels of true positives and true negatives in the SVM model are also satisfactory. Among decision trees and the ensemble model, the Decision Tree model also shows the ability to discriminate between normal operation and maintenance needs . However, there seems to be a small difference in the fact that the number of false positives and false negatives is a little higher in the decision tree, while the number of its true positives and true negatives remains high as in the Random Forest model. In general, the confusion matrices provide clear knowledge of how well each of the models can classify the induction motor health status and inform the predictive maintenance.

The figure 5 and 6 illustrates the results obtained by the performance of each Machine Learning model by epochs from 10 to 400. The epochs for the Artificial Neural Network , Support Vector Machine , Decision Tree , and Random Forest models have compared based on their accuracy and data loss. The data obtain valuable insights into the behavior of the model convergence and their impact on the training process. For accurate, high values mean better performance, while for the data loss, low values mean better. From the iterations it is seen that the ANN model is excellent in predicting the responses.

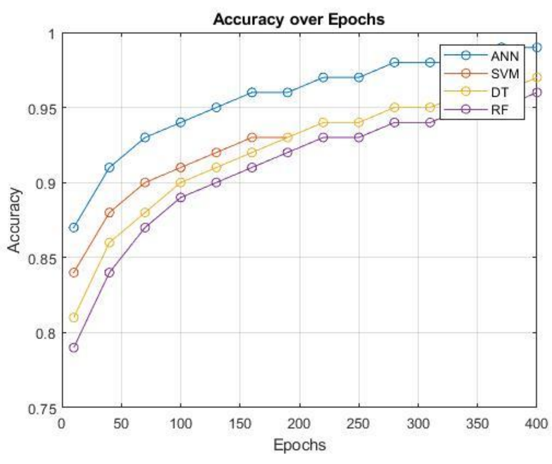

Figure. 5. Accuracy of each model

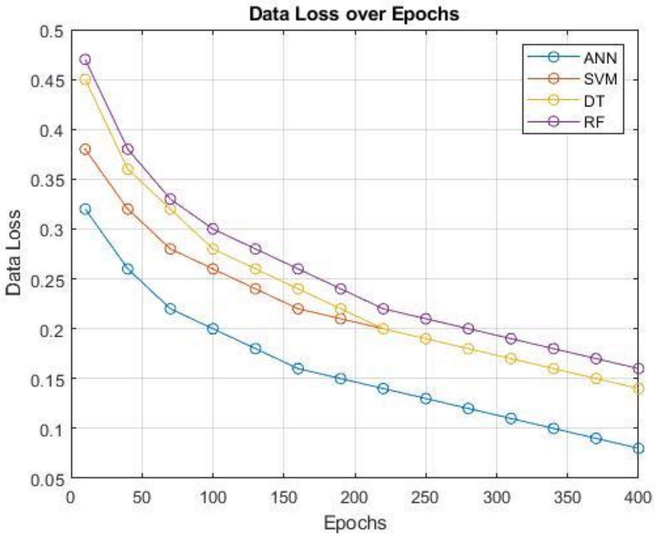

Figure 6. Data loss of each model

V. CONCLUSION

The research focused on data-driven thermal monitoring of induction motors in electrified powertrains. Thus, it is crucial for improving the reliability, efficiency, and longevity of electric vehicle powertrains . By incorporating a range of sensor systems and rigorous ML algorithms, we provided new insights and novel approaches to predictive maintenance and operation optimization. Our findings demonstrated the applicability of numerous ML-based approaches to perform accurate long- and short-term predictions of maintenance needs as well as optimization of the operation of the coolant pump through real-time sensor fusion. The detailed examination of their performance and comparison in the context of comparison to ANNs, SVMs, DTs, and RFs also helped to identify subtle details of each models' advantages and limitations to a greater extent, which helped to make the decision regarding the most appropriate model type and optimization strategy. Additionally, experiments and evaluations of the performance of ML models through various numbers of epochs can help to gain insights regarding the specifics of their training and convergence. The key observed trends suggest that further increasing the number of epochs may not lead to improvements in the overall model performance and the adopted metrics. Thus, our research made use of cloud computing and wireless communication technologies for implementing scalable and highly efficient solutions for induction motor thermal monitoring. The scalability can be particularly important in the context of the growing market of electrified powertrains where innovations in predictive maintenance strategies and operation efficiency may benefit from our results in future deployments. This research may also be considered as a starting point for further improvements and innovations in electric powertrain maintenance strategies. Moreover, additional sensor systems and fusion mechanisms can result in further performance improvements as evidenced by the results of this study.

REFERENCES

[1] H. Mirshekali, A. Keshavarz, R. Dashti, S. Hafezi, and H. R. Shaker, "Deep learning-based fault location framework in power distribution grids employing convolutional neural network based on capsule network," *Electric Power Systems Research*, vol. 223, no. May, p. 109529, 2023, doi: 10.1016/j.epsr.2023.109529.

[2] C. Vennila *et al.*, "Forecasting Solar Energy Production Using Machine Learning," *International Journal of Photoenergy*, vol. 2022, 2022, doi: 10.1155/2022/7797488.

[3] W. Sun, P. Hu, F. Lei, N. Zhu, and Z. Jiang, "Case study of performance evaluation of ground source heat pump system based on ANN and ANFIS models," *Applied Thermal Engineering*, vol. 87, pp. 586–594, 2015, doi: 10.1016/j.applthermaleng.2015.04.082.

[4] M. Taoufik and S. Lassad, "Experimental stand-alone self-excited induction generator driven by a diesel motor," *Journal of Electrical Systems and Information Technology*, vol. 4, no. 3, pp. 377–386, 2017, doi: 10.1016/j.jesit.2016.08.005.

[5] A. S. Yeardley, J. O. Ejeh, L. Allen, S. F. Brown, and J. Cordiner, "Integrating machine learning techniques into optimal maintenance scheduling," *Computers and Chemical Engineering*, vol. 166, no. August, p. 107958, 2022, doi: 10.1016/j.compchemeng.2022.107958.

[6] L. Magadán, F. J. Suárez, J. C. Granda, and D. F. García, "Low-cost real-time monitoring of electric motors for the Industry 4.0," *Procedia Manufacturing*, vol. 42, no. 2019, pp. 393–398, 2020, doi: 10.1016/j.promfg.2020.02.057.

[7] R. Rudrapati, “Using industrial 4.0 technologies to combat the COVID-19 pandemic,” *Annals of Medicine and Surgery*, vol. 78, no. May, p. 103811, 2022, doi: 10.1016/j.amsu.2022.103811.

[8] L. He, “Industry 4.0 Oriented Distributed Infographic Design,” *Mobile Information Systems*, vol. 2022, 2022, doi: 10.1155/2022/4743216.

[9] M. Sujatha *et al.*, “IoT and Machine Learning-Based Smart Automation System for Industry 4.0 Using Robotics and Sensors,” *Journal of Nanomaterials*, vol. 2022, 2022, doi: 10.1155/2022/6807585.

[10] Y. Liu and Z. Ping, “Research on Brand Illustration Innovative Design Modeling Based on Industry 4.0,” *Computational Intelligence and Neuroscience*, vol. 2022, 2022, doi: 10.1155/2022/7475362.

[11] L. W. Qin *et al.*, “Precision Measurement for Industry 4.0 Standards towards Solid Waste Classification through Enhanced Imaging Sensors and Deep Learning Model,” *Wireless Communications and Mobile Computing*, vol. 2021, 2021, doi: 10.1155/2021/9963999.

[12] F. Tao, Q. Qi, L. Wang, and A. Y. C. Nee, “Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison,” *Engineering*, vol. 5, no. 4, pp. 653–661, 2019, doi: 10.1016/j.eng.2019.01.014.

[13] W. Jiang, “A Machine Vision Anomaly Detection System to Industry 4.0 Based on Variational Fuzzy Autoencoder,” *Computational Intelligence and Neuroscience*, vol. 2022, 2022, doi: 10.1155/2022/1945507.

[14] E. Oztemel and S. Gursev, “Literature review of Industry 4.0 and related technologies,” *Journal of Intelligent Manufacturing*, vol. 31, no. 1, pp. 127–182, 2020, doi: 10.1007/s10845-018-1433-8.

[15] T. Kegyes, Z. Süle, and J. Abonyi, “The Applicability of Reinforcement Learning Methods in the Development of Industry 4.0 Applications,” *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/7179374.

[16] A. Binbusayyis and T. Vaiyapuri, “A professional-driven blockchain framework for sharing E-Portfolio in the context of Industry 4.0,” *ICT Express*, no. xxxx, 2022, doi: 10.1016/j.icte.2022.03.010.

[17] A. Jamwal, R. Agrawal, and M. Sharma, “Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications,” *International Journal of Information Management Data Insights*, vol. 2, no. 2, 2022, doi: 10.1016/j.jjimei.2022.100107.

[18] G. Rathee, M. Balasaraswathi, K. P. Chandran, S. D. Gupta, and C. S. Boopathi, “A secure IoT sensors communication in industry 4.0 using blockchain technology,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 1, pp. 533–545, 2021, doi: 10.1007/s12652-020-02017-8.

[19] E. Mueller, X. L. Chen, and R. Riedel, “Challenges and Requirements for the Application of Industry 4.0: A Special Insight with the Usage of Cyber-Physical System,” *Chinese Journal of Mechanical Engineering (English Edition)*, vol. 30, no. 5, pp. 1050–1057, 2017, doi: 10.1007/s10033-017-0164-7.

[20] M. Ammar *et al.*, “Significant applications of smart materials and Internet of Things (IoT) in the automotive industry,” *Materials Today: Proceedings*, vol. 68, pp. 1542–1549, 2022, doi: 10.1016/j.matpr.2022.07.180.

[21] L. Sha, F. Xiao, W. Chen, and J. Sun, “IIoT-SIDefender: Detecting and defense against the sensitive information leakage in industry IoT,” *World Wide Web*, vol. 21, no. 1, pp. 59–88, 2018, doi: 10.1007/s11280-017-0459-8.

[22] S. B. Rane and Y. A. M. Narvel, “Data-driven decision making with Blockchain-IoT integrated architecture: a project resource management agility perspective of industry 4.0,” *International Journal of System Assurance Engineering and Management*, vol. 13, no. 2, pp. 1005–1023, 2022, doi: 10.1007/s13198-021-01377-4.

[23] K. P. Paranitharan, G. Ebenezer, V. Balaji, M. Adham Khan, and T. Ramesh Babu, “Application of industry 4.0 technology in containing Covid-19 spread and its challenges,” *Materials Today: Proceedings*, vol. 68, pp. 1225–1232, 2022, doi: 10.1016/j.matpr.2022.06.009.