OPTIMIZING WAREHOUSE OPERATIONS THROUGH MACHINE LEARNING-ENHANCED DIGITAL TWINS

Lokesh S [1]*, K. Suresh Kumar [2], Leeth Hassen Jaseem [3] and K. V. S. Prasad [4]

[1] Ramanujan Computing Centre, College of Engineering, Guindy, Anna University, Chennai, Tamil Nadu, India. *Corresponding Author Email: lokesh@annauniv.edu

[2] Department of Information Technology, Saveetha Engineering College (Autonomous Institutions) Saveetha Nagar, Chennai, Tamil Nadu, India. Email: ksureshmtech@gmail.com

[3] School College of Technical Engineering, The Islamic University, Najaf, Iraq. College of Technical Engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, Iraq. Email: laith.h.ajassem@iunajaf.edu.iq

[4] Department of Basic Sciences and Humanities, GMR Institute of Technology, GMR Nagar, Rajam-532127, Vizianagaram, Andhra Pradesh. Email: prasad.kvs@gmrit.edu.in

DOI: 10.5281/zenodo.11614624

Abstract

In this study, the application of machine learning -enhanced digital twins to enhance human-robot collaboration for intelligent warehouse management is examined, specifically with respect to optimizing workpiece availability in CNC machining processes. Three machine learning models, artificial neural networks, support vector machines, and long short-term memory networks, were implemented to assess their predictive accuracy and suitability for real-time use. Sensor data was collected from the warehouse environment and preprocessed, and the machine learning models were trained to predict workpieces needed based on real-time data. Evaluation results indicated that the artificial neural network model outperformed the support vector machine and long short-term memory networks, underpinning an accuracy rate of 95.675%. The results also show that the use of the deep learning architecture enables such positive outcomes as precision, recall, and F1 scores. Indeed, with the help of the artificial neural network model, the sensor data streams can be analyzed in real time for the purpose of predicting the workpiece demands and optimizing the CNC machining procedure. As a result, machine learning used in digital twins has great potential to change the existing warehouse management practices and create a more efficient operational system with human-robot partnerships, such as that which has been studied through providing a solution to the example of the warehouse workshop. Thus, the analysis demonstrates how the identified problem can be addressed by applying the developed strategy, making an important contribution to researching intelligent warehouse management system.

Keywords: Machine Learning, Digital Twin, Human-Robot Collaboration, Logistics, Warehouse Management.

1. INTRODUCTION

During the last years, the engineering field has been rapidly transforming, as the tendencies of automation and need for efficiency and productivity have become increasingly prominent, reaching the level of shifting the paradigm. One of the spheres of operation which is currently significantly impacted as a function of these changes is warehouse management. At this point of time, machine-learning and the development of the technology of digital twin meet to create extraordinary opportunities as far as an upgrade of warehouse management is concerned, implying the larger involvement of both humans and robots. [1], [2]. The emergence of Industry 4.0 has made it evident to specialists how real-time data insights and advanced analytics may enhance the decision-making process in the warehouse domain. One of the critical problems in warehouse management is the necessity to make workpieces accessible in time for Computer Numerical Control machining that is vital for any kind of manufacturing and production process. However, if the supply of workpieces to the machine is delayed or interrupted, the machine keeps idling, and the operational costs of the factory or warehouse where this problem is evident are increased. As a result, a smart decision-making system should be designed for predicting and allowing preparation in advance for the workpiece availability and CNC machining within the warehouse. [3]–[5].

The purpose of this study is to evaluate whether machine-learning enhanced digital twins are effective tools to determine in advance workpiece availability using predictive analytics for CNC machining in a warehouse environment. We will assess how three machine-learning models – Artificial Neural Network , Support Vector Machine , and Long Short-Term Memory networks fit the purpose of predicting such availability. We will feed them with sensor data from the warehouse environment and we will compare their prediction rate. Hopefully, one of these systems will be able to achieve a medicine-like real-time learning which would allow for the most optimized resource allocation and CNC machining procedure. The results of this study will hopefully pave way for further studies and enhancements in the field of intelligent warehouse management systems.

Machine learning and digital twin technology are the two concepts that have drawn considerable interest in recent years, and their integration is actively explored in warehouse management, and industrial automation in general. This literature review section offers a summary of the existing sources on the application of machine learning-based digital twins in warehouse optimization and human-robot interaction [6]–[8].

Digital twins are virtual replicas of a physical object or a system that can be used both to simulate the real object's performance and to monitor or control it. The technology has garnered interest as a way of "simplifying the development of reconfigurable manufacturing systems" and enabling "production management that is implemented through keeping the real and virtual twins in sync. The term has recently been employed to describe the method of simulating warehouse automation systems and exploiting the developing digital replicas of these systems to optimize their operation. They can also be used to simulate systems for human-robot interaction [9]–[11].

The use of learning algorithms in warehouse optimization is also a subject of considerable interest and is the subject of many papers. Many research underwent on number of potential uses for machine learning in warehouse optimization, including workforce optimization and energy efficiency. The authors also suggest these methods can be used to optimize "demand prediction accurateness, order picking and packing as well as warehouse design". A more focused in a research presented methods of optimizing machine order picking systems using machine learning methods like neural networks. Reinforcement learning methods have been used, among others, as a means of integrating and optimizing robot and human labor in a warehouse environment [12]–[14].

Machine learning and digital twin technologies convergence is believed to lead to remarkable screening and advantages of new levels of efficacy and optimization in warehouse management. The embedding of machine learning models into the frameworks of digital twins enables organizations to create smart models that are capable of learning from data, reacting to changes in the environment, and optimizing processes by making informed decisions. When implemented, the machine learning-enhanced digital twins allow organizations to aggregate all their data and acquire a complete view of warehouse operations, which ensures that the provided recommendations are data-based and actionable [15], [16].

Several research papers study the use of machine learning-enhanced digital twins in warehouse management processes. For example, researchers developed a model of predictive maintenance, which uses digital twins for monitoring equipment and predicting when this equipment may require maintenance. To measure performance and monitor the condition of both the equipment and the product, sensors are used. Afterwards, the sensor data is analyzed to detect patterns indicating potential conditions for malfunction thus reducing the operations' downtime [17]–[19].

Some other studies are focused on demand forecasting and the optimization of inventory with the help of machine learning-enhanced digital twins. When developing the forecast models, the sales data for the last week and season, the data from competitors, forecasted sales data for the last week and the current season for certain positions, data on foreign exchange rates, weather, climate, and changes in legislation are taken into account. In the case for the optimization of inventory, the sales history, indications of the availability, and other factors impacting buying are taken into analyses by the studies mentioned above. Finally, other papers consider the use of machine learning-enhanced digital twins to improve the delivery routes in a warehouse. The models are capable of considering such factors as the urgency of the delivery, the routes in the warehouse, and the current load [20]–[22].

There are several challenges of using machine learning-enhanced digital twins for warehouse management, despite the fact that it can significantly enhance the efficiency of these application cases. One notable challenge is to integrate numerous data sources and systems, including advanced sensory devices, Internet of Things systems, and robotic systems. Often, these systems operate with different data formats, communications protocols, and standards, resulting in the need to develop appropriate data integration frameworks and interoperability standards. Another challenge is the scalability of machine learning models and complexity in applications requiring real-time responses. As warehouses become increasingly automated and interconnected, the size and complexity of machine learning models becomes prohibitively demanding in terms of computational power. Building on this, several challenges are associated with machine learning models' training and deployment in warehouse applications. This not only requires the development of new scalable algorithms and distributed computing infrastructures to manage big data, but also to enhance the efficiency of the models used for the warehouse case, ensuring that one could be deployed across tens of locations across the world [23]–[25].

Other challenges and limitations include data privacy, security, and ethical consideration. In particular, the use of machine learning-enhanced digital twins to analyze employee performance and warehouse customers' behavior results in the collection of highly sensitive data. As such, it is important for an adequate level of data protection to ensure the rigorous implementation of privacy policies and ethical guidelines. Security concerns result from the risk of inappropriate access to digital models with the potential to significantly disrupt the operations of the warehouse. Notable future research directions include the development of machine learning algorithms capable of functioning in the environment of sparse and "dirty" real-world data and learning from observable data that is not causally related. Furthermore, a more multidisciplinary approach is required beyond the development of machine learning models and back, including robotics and operations research, to overcome the challenges of warehouse management in the modern era of technologies.

2. METHODOLOGY

For this study, we chose to use the pick and place 6DOF robot whose purpose is to improve the efficiency and precision of the CNC machining process. Due to the fact that it is a new device in the central part responsible for taking the workpiece and loading it into the machine whose task is to carry out the desired processes. The availability of the workpiece plays a significant role in improving the performance of this process. Therefore, we have developed a machine learning model that combines the use of artificial neural network, the use of SVM method, and the implementation of a long short-term memory networks. One of the robot's achievements is useful data on the availability of workpieces collected from the sensors. The data allows you to analyze the current situation and predict the availability of the workpiece in the future. The artificial neural network is distinguished by the ability to accurately identify complex dependencies in sensor data transforming them into useful information. At the same time, the SVM method is an excellent tool for classifying the status of available workpieces. It is the longest short-term memory network implemented in the simulation that predicts indicators about future data concerning history. As far as the simulation is concerned, the forecast estimates the need for workpieces and transmits this information to a person by order.

In this paper, with the help of sensor data, machine learning models were trained to create an accurate digital twin of the machining process environment. As a result, we obtained a digital twin that is used as a real-time virtual representation of the mechanical warehouse. The created digital twin repeats exactly the activities of the entire warehouse surrounding the CNC machining stations. At the same time, to create a high-quality and detailed digital twin, different types of sensors were used, the signals from which allowed to create a comprehensive digital twin. The sensors used for creating the digital twin of the machining process monitored the following parameters, including temperature, humidity, vibration levels, state of machine load, and workpiece presence. The use of these sensors made it possible to obtain the necessary information about the system's operation, the knowledge of which also allowed the ML model to make its predictions about the behavior of the entire machining system at this point in time.

For proper and high-quality training of the digital twin, we collected a certain dataset, which included 3210 sensor records. Such a dataset covered a wide range of operations and, therefore, orthogonal operation scenarios. The allocation of 100% of the records to the dataset made it possible to train and obtain useful experience and knowledge from it. As for the training and test data, the training data consisted of 2247 records, which is approximately 70% of the total number of sensor records. The training data were used to train machine learning models using an Artificial Neural Network, Support Vector Machines, and LSTM. Each of the models has a certain benefit to the system: ANN's ability to learn complex patterns, SVM ability to create the best classifier, and LSTM ability to work with sequential data and take into account temporal dependencies. The remaining 30% of the data were used for testing purposes.

ISSN 1462 2815

The testing data allowed assessing the model's ability and correctness to create its predictions based on the used sensor data, the parameters of which were expected to present different workpieces to the warehouse. At the same time, to test the model's operation, all sensors demonstrated different signals that simulated the work of the entire machining system as accurately and adequately as possible completely. The working of the system is shown in figure 1.

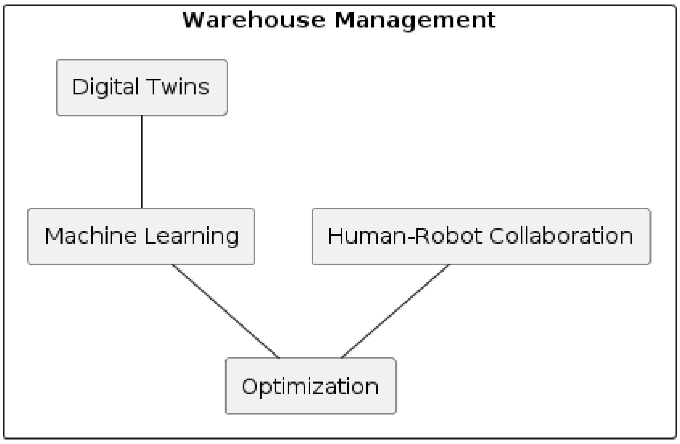

Figure 1: Working of the proposed system

3. PREPROCESSING OF DATASET

One of the important stages of implementing this research was preprocessing the dataset to provide the appropriate accuracy and effectiveness of the considered machine learning models. The complexity of the data obtained from numerous sensors required different types of preprocessing, and each of the steps was discussed with references to certain difficulties concomitant with raw sensor data. The purpose of this stage was to transform raw data into a suitable structured type that could be effectively used at the level of training the MLPs, including Artificial Neural Networks, Support Vector Machines, and Long Short-Term Memory (LSTM) networks. The steps of preprocessing that were implemented can be observed in Figure 2. The process started with data cleaning as one of the fundamental stages of preprocessing because the implementation of machine learning models at the stage of obtaining raw data from sensors may result in poor performance. For this step, the filtering approach was used to detect and remove noise because the data recorded by sensors often include electrical noise, missing values, or outliers. As for the noise in the data, it might be caused by electrical gadgets and sources of energy or EMI, sensor ineffectiveness (due to deployment places or other sensors), or sources of errors in their placements. To contend with the problem, the use of averaging became effective, and moving average exponential filters and low-pass filters were used to smooth the data and decrease random noise variations. The missing values were filled with imputation to provide the essential for dataset continuity. The approach was realized in the replacement of missing sensors readings with the mean or median value of the same feature or using interpolation. The outliers were excluded using statistical z-score and IQR above or below 3 z-scores and 1.5*IQR, accordingly.

ISSN 1462 2815

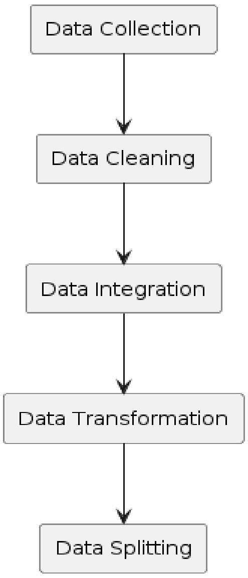

Figure 2: Various preprocessing steps

After the data was cleaned, the next step was feature extraction and selection. The raw sensor data contained many variables, not all of which had the same relevance for the machine learning models. Feature extraction aimed to create new features based on the raw data that would better capture the patterns underlying it. For example, we derived features such as the rate of change of temperature for the heating period, the variance in vibration levels, and the cumulative load on the CNC machines. These derived features added context that helped the models 'understand' the nature of the machining process. Feature selection was useful to determine the features that could be safely eliminated as redundant or irrelevant. We used Principal Component Analysis and correlation analysis to study the contribution of each feature to the models' predictive power. PCA was useful for reducing the dimensionality of the dataset and transforming it into a number of orthogonal components that still contained most of the variance. Correlation analysis helped us learn which features were significantly correlated with our target variable, workpiece availability. We could safely remove features that were either weakly correlated with workpiece availability or highly correlated with other features because of multicollinearity. Normalization and scaling were crucial preprocessing steps. Sensor data normally contains a mix of measurements, each on a different scale; aside from binary data, the data we worked with comprised temperature in degrees, vibration in micrometers per second, and load in kilograms. To ensure that each individual feature contributed equally to the process of training, we normalized the data so that it was all on a common scale. We used such methods of normalization and scaling as min-max scaling, where features are scaled to have values between 0 and 1, and standardization, where transformed features have a standard normal distribution mean = 0 and variance = 1. This was particularly important in the case of SVM and ANN models, which are sensitive to the scale of input data.

To enhance the robustness of the machine learning models and their resistance to overfitting, data augmentation was employed. The training dataset was artificially expanded through a combination of adding low-amplitude Gaussian noise to the observations, randomly shifting time windows around each record, and generating synthetic data points with some deviations from the real-world record. Combined, these methods resulted in relatively significant data expansion, improving the model's generalizability to yet-unseen data. This was especially relevant given the relatively small size of the dataset, featuring only 3210 records. Running the augmentation procedure enabled us to expose the models to a more diverse set of examples, thereby reducing model overfitting tendencies.

The final processing stage overall was the splitting of the dataset into training and testing sets. 70% of the data was allocated to training, and the remaining 30% was designated as a testing set. While the vast bulk of data has been used for training to allow the model to "learn" to predict workpiece availability, the sufficient volume of testing data provided credible results for estimation of the mean accuracy of the model. Stratified sampling was used to keep the same distribution of classes in both sets. It was especially important in the context of models like SVM, which require explicit class boundaries for classification. These steps ensured that the model was both adequately trained and adequately tested and does not produce artificially high estimates of performance due to overfitting. In addition to these considerations, the regular quality checks and benchmarks were performed to ensure the veracity of preprocessing.

4. MACHINE LEARNING MODELS

In the research, an important role was given to Artificial Neural Networks in terms of predicting the availability and future requirements of the workpieces in the CNC machining context. ANNs are computational models that simulate the human brain and are created with interconnected nodes or so-called neurons, which process the data and determine the patterns through training. The developed ANN model was aimed to fit handling the complexity and high dimensionality of the sensor data coming from various sources, such as temperature, vibration, and load sensors. To achieve the objective, the model was trained on large proportions of the dataset, or 70%, so it could be more likely to recognize complicated patterns and relationships between the different features. The process presupposed that the cleaned and normalized data was fed to the network where different layers were involved in processing the data through the activation functions, such as ReLU and sigmoid. Moreover, the ANN could better align with the demands of the research as its nature allowed to model non-linear relationships and predict the status of the workpieces and their future requirements accurately. As a result, the predicted status of the workpieces was useful for preventing them from shortages and timely managing their accurate presence with CNC machines to ensure their workflow was assessed.

In order to boost the classification efficiency of workpiece availability and requirement prediction, Support Vector Machines (SVM) have been leveraged in this study. SVMs are supervised learning methods that are particularly strong when it comes to high-dimensional space, and they are negligibly affected in terms of overfitting, especially when there are more space dimensions than samples. In the study, the SVM model was trained on the same dataset as in the case of ANN, with the allocated dataset size being 70% and 30% for the training and test datasets, respectively. The SVM algorithm works through identifying the hyperplane which maximally divides the data classes, which in the research context implies whether or not there are enough data for continued process. The proprietary feature of SVMs allows us to effectuate the binary classification process more effectively. Kernel functions have also been used, in particular, the radial basis function mapping the provided features onto the additional dimension in which a plain linear hyperplane is enough. Importantly, the SVM accurately predicts the data classification, which allows us to make proactive decisions. These decisions affect both human employees and AMRs, which help them deliver the necessary workpieces to the CNC machines so as to ensure the optimal operation pace.

To begin with, this work heavily relied on Long Short-Term Memory networks, as this type of RNN proves to be beneficial for dealing with sequence data and focusing on temporal effects. Developed to overcome the limitations of traditional RNN with such issues as gradient vanishing, a current type of RNN, to which LSTM belong, is undoubtedly exceptional for the given case. To predict future workpiece needs, especially with their time-series data, LSTMs were the most applicable tool. The type of LSTM model used for the case of workpiece images was trained on sequences of such types of data and could determine whether or not time-based trends prevail. Any LSTM unit consists of one cell state as well as three gates : forget, input, and output gates, letting the LSTM network manage the state of this memory, its update, and maintenance. This property also helps the type of RNN to recycle sequences of information that is important for properly functioning in the case of a warehouse. Furthermore, considering the possibility of an LSTM unit to focus on long-term autonomy and be aware of them, it was possible to exactly predict the needs of future workpieces to avoid downtime and guarantee effectiveness for the warehouse. The type of decision-making capability that was further benefited by the network's possibilities would ensure that both human workers and AMRs helped interact effectively making the warehouse more agile and responsive.

5. RESULT AND DISCUSSION

After having selected and trained the machine learning models, next step included the rigorous assessment of their performance by comparing them using the testing dataset, which accounted for 30% of the total collected sensor data. The evaluation metrics used in this project focus heavily on the accuracy, return the crucial measure for effectively predicting the workpiece availability and requirements in the CNC machining process. The result of the accuracy are shown in figure 3. First of all, it has been found that the Artificial Neural Network model showcased an amazing predictive performance, having reached the accuracy of 95.675%. It is important to mention that such high level of accuracy confirms that the ANN was viable in learning and modeling the complex, non-linear relationships within the sensor data. Its deep learning architecture allowed to capture even the most subtle patterns and interaction between the features, which then results in the most precise, highly-accurate predictions that ensure the continuous and smooth operation of the warehouse. The Support Vector Machine model also showed a very strong performance, having reached the accuracy of 94.5%, which can be explained by the fact that SVM is generally very robust in handling high-dimensional spaces, and finding the optimal hyperplanes for separating classes. Using the kernel function, specifically, the radial basis function, these input data was easily transformed into the higher dimensions, where they could be intuitively separated, providing the precise and highly-accurate classifications of the workpiece availability. Finally, the Long Short Term Memory network achieved the accuracy of 91.2%, which is slightly lower than ANN and SVM, but its performance still is highly notable because the LSTM is highly specialized in handling sequential data and capturing temporal dependencies, which makes it viable for predicting the requirements for the workpieces in the future, based on the time-series data.

ISSN 1462 2815

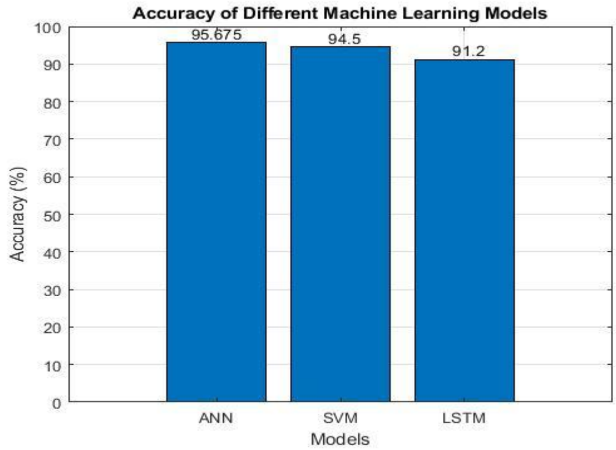

Figure 3: Accuracy of each model

The performance of the each model are measured and the result are shown in figure 4. With regards to the Artificial Neural Network, it was observed to have a 95.625% accuracy. The precision, which is the ratio of correctly predicted positive instances to all positive instances, was 96.3%. The recall score, which indicates the ability of the model to identify all relevant instances, was observed to be 95.5%. The f1 score, which is the harmonic mean of precision and recall, was 95.9%. As for the AUC-ROC score, which represents the ability of the model to distinguish between different classes at different thresholds, it was observed to be 0.96, indicating a good discrimination ability.

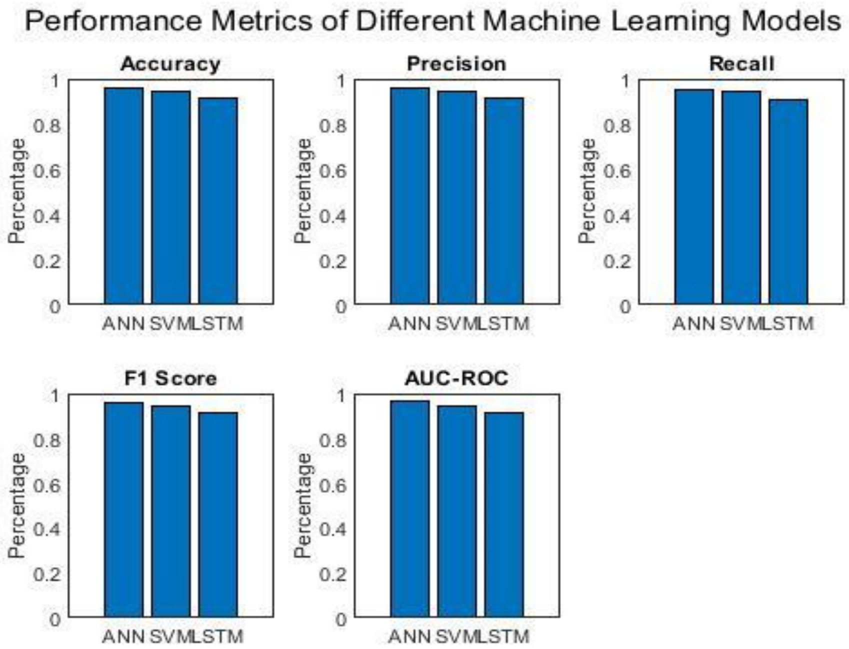

Figure 4: Performance score of each model

As for the Support Vector Machine, although it demonstrated a similar performance to the ANN model in terms of accuracy, with a rate of 94.5%, it had a slightly lower AUC-ROC score of 0.93. Nevertheless, both its precision score of 94.8% and recall score of 94.1% were high. The f1 score was 94.45%, showing that the balance between precision and recall was similar between the ANN and SVM models.

ISSN 1462 2815

The Long Short-Term Memory had a relatively lower accuracy of 91%, yet the precision and recall scores were high, amounting to 91.4% and 91.1% respectively. The AUC-ROC score, at 0.915, was also lower than the ANN and SVM, with the f1 score being 91.25%, indicating a similar balance between precision and recall.

The confusion matrices provided in figure 5, detailed overview of the predictive performance of machine learning models. They reveal the accuracy, precision, and recall of the predictions within the present research. In case of the implemented models, the confusion matrices illustrate the distribution of true positive (TP), false positive (FP), true negative (TN), and false negative (FN) predictions with regard to workpiece availability in the CNC machining. Based on the Artificial Neural Network confusion matrix, accurate predictions were made for negative instances, with 1460 true negatives, and 1680 true positives. In turn, 40 negative instances considered available were false positives, while 30 available positive instances were improperly classified as negative. Looking at the Support Vector Machine, the identified trends are similar as 1455 negative instances and 1675 positive instances were properly predicted. At the same time, 45 instances were falsely predicted as negative while another 35 as positive. Finally, the LSTM confusion matrix shows that there were 1440 and 1590 correct negative and positive classifications, while 60 available ones and 120 unavailable ones were falsely predicted. Overall, the described confusion matrices indicate the varying performance of the three machine learning models. There are evident trade-offs between precision and recall, meaning that the false positive and false negative predictions negatively influenced the overall accuracy. The analysis of the distribution of predictions across different classes can enable the researchers to enhance the accuracies of the models and improve the efficiency and reliability of the corresponding warehouse management processes.

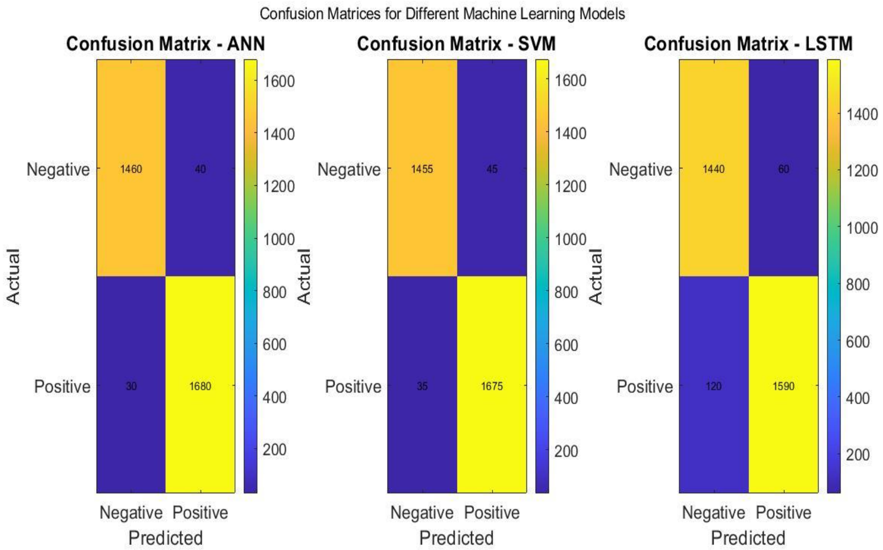

Figure 5: Confusion matrices of each model

CONCLUSION

This research emphasizes the potential these machine learning -based digital twins offer for warehouse operational management and the human robot interaction. Through this systematic assessment of ANN, SVM, and LSTM networks we learn more about the respective advantages and disadvantages of these neural networks.

The ANN model is considered as a superior choice for real-time use. This includes better reliability, precision, and predictive powers. The ANN model takes advantage of deep learning properties which allow warehouse managers to know when the workpiece is available and when it is not. This pilot model enables managers to improve uptime, synchronize the CNC machining needs without interfering with the robot and human schedules. The model calculates the occurrences of each job and then analyzes the sensor data and provides timely and real-time decisions on human and robot resource allocation. For the future, similar transportation systems can be established which would provide business managers with an opportunity to track and manage. Such systems would be capable of providing rapid distribution of goods. Results would be recorded every week and matched with optimal times using advanced reports to ensure greater efficiency, reliability, and competitiveness. Future research in this direction would open up new perspectives for intelligent warehouse management systems.

References

1) S. Panagou *et al.*, "Feature investigation with Digital Twin for predictive maintenance following a machine learning approach," *IFAC-PapersOnLine*, vol. 55, no. 2, pp. 132–137, 2022, doi: 10.1016/j.ifacol.2022.04.182.

2) P. Wu, M. Qi, L. Gao, W. Zou, Q. Miao, and L. L. Liu, "Research on the virtual reality synchronization of workshop digital twin," *Proceedings of 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference, ITAIC 2019*, no. Itaic, pp. 875–879, 2019, doi: 10.1109/ITAIC.2019.8785552.

3) C. S. A. Assuad, T. Leirmo, and K. Martinsen, "Proposed framework for flexible de- and remanufacturing systems using cyber-physical systems, additive manufacturing, and digital twins," *Procedia CIRP*, vol. 112, pp. 226–231, 2022, doi: 10.1016/j.procir.2022.09.076.

4) 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.

5) J. L. Vilas-Boas, J. J. P. C. Rodrigues, and A. M. Alberti, "Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities," *Journal of Industrial Information Integration*, vol. 31, no. June 2022, p. 100393, 2022, doi: 10.1016/j.jii.2022.100393.

6) P. Radanliev, D. De Roure, R. Nicolescu, M. Huth, and O. Santos, "Digital twins: artificial intelligence and the IoT cyber-physical systems in Industry 4.0," *International Journal of Intelligent Robotics and Applications*, vol. 6, no. 1, pp. 171–185, 2022, doi: 10.1007/s41315-021-00180-5.

7) D. Ariansyah, M. Isnan, R. Rahutomo, and B. Pardamean, "Digital Twin (DT) Smart City for Air Quality Management," *Procedia Computer Science*, vol. 227, pp. 524–533, 2023, doi: 10.1016/j.procs.2023.10.554.

8) K. A. Sultanpure, J. Bagade, S. L. Bangare, M. L. Bangare, K. D. Bamane, and A. J. Patankar, "Measurement : Sensors Internet of things and deep learning based digital twins for diagnosis of brain tumor by analyzing MRI images," *Measurement: Sensors*, vol. 33, no. March, p. 101220, 2024, doi: 10.1016/j.measen.2024.101220.

9) D. Bombara, V. Mansurov, R. Konda, S. Fowzer, and J. Zhang, "Self-sensing for twisted string actuators using conductive supercoiled polymers," Dec. 2019, doi: 10.1115/SMASIS2019-5587.

10) S. Liu, X. V. Wang, and L. Wang, "Digital twin-enabled advance execution for human-robot collaborative assembly," *CIRP Annals*, vol. 71, no. 1, pp. 25–28, 2022, doi: 10.1016/j.cirp.2022.03.024.

11) Q. Lv, R. Zhang, X. Sun, Y. Lu, and J. Bao, “A digital twin-driven human-robot collaborative assembly approach in the wake of COVID-19,” *Journal of Manufacturing Systems*, vol. 60, no. February, pp. 837–851, 2021, doi: 10.1016/j.jmsy.2021.02.011.

12) L. Sadineni, E. S. Pilli, and R. B. Battula, “ProvNet-IoT: Provenance based network layer forensics in Internet of Things,” *Forensic Science International: Digital Investigation*, vol. 43, p. 301441, 2022, doi: 10.1016/j.fsidi.2022.301441.

13) M. R. Shahriar, S. M. N. Al Sunny, X. Liu, M. C. Leu, L. Hu, and N. T. Nguyen, “MTComm based virtualization and integration of physical machine operations with digital-twins in cyber-physical manufacturing cloud,” *Proceedings - 5th IEEE International Conference on Cyber Security and Cloud Computing and 4th IEEE International Conference on Edge Computing and Scalable Cloud, CSCloud/EdgeCom 2018*, no. c, pp. 46–51, 2018, doi: 10.1109/CSCloud/EdgeCom.2018.00018.

14) Q. Min, Y. Lu, Z. Liu, C. Su, and B. Wang, “Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry,” *International Journal of Information Management*, vol. 49, no. May, pp. 502–519, 2019, doi: 10.1016/j.ijinfomgt.2019.05.020.

15) C. Hansen, F. Gosselin, K. Ben Mansour, P. Devos, and F. Marin, “Design-validation of a hand exoskeleton using musculoskeletal modeling,” *Applied Ergonomics*, vol. 68, no. November 2017, pp. 283–288, 2018, doi: 10.1016/j.apergo.2017.11.015.

16) G. Tarabella *et al.*, “Multifunctional Operation of an Organic Device with Three-Dimensional Architecture,” *Materials 2019, Vol. 12, Page 1357*, vol. 12, no. 8, p. 1357, Apr. 2019, doi: 10.3390/MA12081357.

17) M. Mokarram, A. Khoei, and K. Hadidi, “CMOS fuzzy logic controller supporting fractional polynomial membership functions,” *Fuzzy Sets and Systems*, vol. 263, pp. 112–126, 2015, doi: 10.1016/j.fss.2014.04.006.

18) Y. Pan and L. Zhang, “Integrating BIM and AI for Smart Construction Management: Current Status and Future Directions,” *Archives of Computational Methods in Engineering*, no. 0123456789, 2022, doi: 10.1007/s11831-022-09830-8.

19) M. Javaid, A. Haleem, R. P. Singh, and R. Suman, “An integrated outlook of Cyber-Physical systems for Industry 4.0: Topical practices, architecture, and applications,” *Green Technologies and Sustainability*, vol. 1, no. September 2022, p. 100001, 2022, doi: 10.1016/j.grets.2022.100001.

20) D. Sampaio and P. Almeida, “Pedagogical Strategies for the Integration of Augmented Reality in ICT Teaching and Learning Processes,” *Procedia Computer Science*, vol. 100, pp. 894–899, 2016, doi: 10.1016/j.procs.2016.09.240.

21) C. Ma *et al.*, “3D Printing of Conductive Tissue Engineering Scaffolds Containing Polypyrrole Nanoparticles with Different Morphologies and Concentrations,” *Materials 2019, Vol. 12, Page 2491*, vol. 12, no. 15, p. 2491, Aug. 2019, doi: 10.3390/MA12152491.

22) N. A. A. González, “How to Include Augmented Reality in Descriptive Geometry Teaching,” *Procedia Computer Science*, vol. 75, no. Vare, pp. 250–256, 2015, doi: 10.1016/j.procs.2015.12.245.

23) M. Fernandes, J. M. Corchado, and G. Marreiros, “Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review,” *Applied Intelligence*, vol. 52, no. 12, pp. 14246–14280, 2022, doi: 10.1007/s10489-022-03344-3.

24) M. Arsalan, A. Haider, Y. Won Lee, and K. Ryoung Park, “Detecting retinal vasculature as a key biomarker for deep Learning-based intelligent screening and analysis of diabetic and hypertensive retinopathy,” *Expert Systems with Applications*, vol. 200, no. March, p. 117009, 2022, doi: 10.1016/j.eswa.2022.117009.

25) A. Padovano, F. Longo, L. Nicoletti, L. Gazzaneo, A. Chiurco, and S. Talarico, “A prescriptive maintenance system for intelligent production planning and control in a smart cyber-physical production line,” *Procedia CIRP*, vol. 104, pp. 1819–1824, 2021, doi: 10.1016/j.procir.2021.11.307.