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Upskilling for Quality 4.0: Competency Models and Micro-credentials for Smart Factories

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Abstract – Industry 4.0 has transformed manufacturing quality by incorporating AI, IoT, and big data for predictive maintenance and operational excellence in smart factories. However, while anomaly detection and maintenance prediction using technical solutions are well advanced, their alignment with workforce competency falls behind. In this paper, COMP-ANN (Competency & Micro-Credential ANN Framework) is introduced as a novel neural network framework integrating real-time IoT anomaly detection, micro-credentialing, and competency mapping in order to facilitate Quality 4.0 workforce development. COMP-ANN is demonstrated on the Smart Manufacturing IoT-Cloud Monitoring dataset to analyze and process sensor data for anomaly detection and maintenance prediction while mapping results to skill-based learning modules at the same time. Comparative evaluation with Isolation Forest, One-Class SVM, and LSTM demonstrates that COMP-ANN outperforms all baselines in Accuracy (98.54%), Precision (98.79%), Recall (98.28%), and F1-score (98.53%). The model holds excellent promise in bridging the gap between intelligent systems and human capital development through enabling scalable upskilling and operational resilience in digital manufacturing ecosystems.

Index Terms – Quality 4.0, Smart Factories, Anomaly Detection, Predictive Maintenance, IoT, Artificial Neural Network, Competency Models, Micro-Credentials, Workforce Upskilling, Industry 4.0

I. INTRODUCTION

Industry 4.0's quick digitization of manufacturing changed the way quality is defined and provided. IoT infrastructures, artificial intelligence, and big data analytics converge in smart factories, which are data-driven establishments that enhance resilience, efficiency, and dependability. In this regard, Quality 4.0 highlights that workforce adaptability is just as critical to organizational success as cutting-edge technology. As a result, competency models and micro-credentialing models are gaining attention as essential tools for mapping human competencies to the constantly evolving demands of digital manufacturing. But the gap still exists. Although AI- and IoT-based environments have demonstrated predictive power in various industrial domains, there remains a limited mapping of these observations to actual workforce competencies. For instance, LSTM-Autoencoders can now function well in low-data factory settings thanks to meta-learning techniques [1]. Similarly, real-time device protection using light models has been accomplished by intelligent IoT anomaly detection systems [2]. Although technically possible, these enhancements rarely involve operators and engineers in the learning process, and it is unclear what capabilities are needed to maintain and expand such systems.

This deficiency is what justifies the present study. Evidence from diverse deployments confirms that predictive maintenance, combined with IoT and AI, can detect anomalies and boundary violations several steps ahead [3]. In the meantime, smart port operations demonstrate that neural network classifiers outperform traditional techniques in fault detection [4]. Advances in deep learning, such as rough set-enhanced LSTMs, have enabled detection accuracy to exceed 94% [5]. At the same time, the use of inexpensive IoT hardware devices and unsupervised learning algorithms demonstrates that effective anomaly detection does not rely on expensive infrastructure [6], and two-stage machine learning pipelines show that even unlabeled IoT data can yield highly accurate predictions [7]. The range and sophistication of technical solutions are demonstrated in each of these studies, along with the absence of precise mechanisms linking such intelligence to workforce competencies and credentialing. To overcome this limitation, we introduce COMP-ANN (Competency & Micro-Credential ANN Framework). To achieve predictive accuracy, this ANN-based IoT anomaly detector integrates its findings into micro-credentialing streams and competency models. This work contributes both organizationally to reskilling the workforce for Quality 4.0 and technically to the state-of-the-art in anomaly detection by benchmarking COMP-ANN against Isolation Forest (IF), One-Class SVM (OCSVM), and LSTM baselines.

The contribution of the paper is as follows:

- We present COMP-ANN (Competency & Micro-Credential ANN Framework). This novel ANN-based IoT anomaly detection model integrates workforce competency mapping, micro-credentialing, and predictive maintenance instantly.
- We develop a methodology that integrates technical intelligence with organized skill development for Quality 4.0 by combining sensor data preprocessing, anomaly detection, and competency alignment.
- Through a comparative evaluation, we demonstrate that COMP-ANN outperforms baseline models, providing consistent, dependable, and comprehensible results for predictive maintenance in smart factories.
- We demonstrate how integrating anomaly detection into competency frameworks can facilitate proactive maintenance, ongoing workforce upskilling, and organizational resilience.

II. LITERATURE SURVEY

The transition to Industry 4.0 and Quality 4.0 has prompted a global reconsideration of workforce development strategies with specific emphasis on reskilling and upskilling to meet the technological and human demands of smart production environments. Central to this shift is the application of micro-credentials and competency-based training models in enabling agile, modular, and lifelong learning systems. This literature review synthesizes current research on micro-credentials' function, alignment to vocational training, and competency modeling as essential drivers to create a future-proofed workforce for industrially driven digital economies.

Walsh Shanahan and Organ [8] identified the strategic potential of micro-credentials as adaptive, skill-based qualifications that address Industry 4.0 and 5.0's fast-evolving demands. Their discussion highlighted the roles of industry–higher education collaborations in developing stackable, guaranteed credentials against frameworks like the European Credit Transfer and Accumulation System (ECTS). Similarly, Siafu [9] has argued that the adoption of industry-led and modular micro-credentials in functional labor markets and the contribution of national standardization frameworks are at the center of their recognition and quality assurance. Wahab et al. [10] also demonstrated how digitalization in logistic and supply chain companies required continuous upskilling, supported by initiatives like Malaysia's Human Resource Development Fund (HRDF) and Competency Management Software (CMS) to trace skill gaps and institute micro-credentialing interventions.

A series of research studies was conducted to close the gap between vocational training and workforce development and competency-based models and pedagogical digitality. Rajuroy [11] presented a modular VET system with simulation tools, digital infrastructure, and industry alliance as a strategy to address training systems and curriculum stalling. Eslamlou et al. [12] developed a competency model using mixed methods and suggested both technical skills and soft skills such as flexibility, creative thinking, and cooperation as the essence of digital readiness for the workforce. Azofeifa et al. [13] introduced the ShapingSkills approach, in which AI and NLP were utilized to offer personalized, adaptive upskilling pathways in Continuing Engineering Education (CEE), mapping the learning path of learners against industry evolving needs. Technology readiness and educational change were also measured for Industry 4.0 contexts elsewhere. Li [14] highlighted the needs of cognitive, digital, and adaptive abilities to propel workforce integration in smart factories and suggested lifelong learning and strategic skill development initiatives. George [15] placed the digital manufacturing revolution through cyber-physical systems, IIoT, and AI and highlighted organizational investment in reskilling the workforce to reduce job replacement and address technological integration challenges. Yaacob et al. [16] surveyed digital proficiency in university students and, of all the predictors for IR 4.0 technology readiness to adopt, concluded information and data literacy to be the most significant, one that could be applied to workforce readiness in smart factories.

Pedota et al. [17] empirically tested the effect of technology adoption on upskilling in enterprises and concluded that Industry 4.0 technology in digital form was more strongly associated with ICT upskilling compared to technology in its physical form. Their research found that the size of an enterprise also determines the extent and breadth of upskilling measures, stressing the need for customised and scalable micro-credential frameworks. Soliani et al. [18] previously had shown a mixed-method evaluation of a Brazilian competency-based training model that addressed technical and soft competences through project-based learning. They could address competency gaps in new technologies such as IoT and robotics and leadership and collaboration within the organization—competencies which characterize Quality 4.0 settings. All the reading matter accessed was regarding micro-credentials and competency-based policies as essential to upskilling in Quality 4.0 cultures. The research studies converged into an agenda of learning a good match between education innovations and industrial transformation through flexibility, digital literacy, and interdisciplinary cooperation. [19] In AI-facilitated learning platforms, vocational-cum-integrated models, or policy-driven national systems, the research overall places itself in finding scalable and agile upskilling programs at the center of prosperity in smart factory environments.

III. METHODS & MATERIALS

3.1 Dataset Description

In this study, we fetched a Kaggle dataset titled *"Smart Manufacturing IoT-Cloud Monitoring Dataset"*, which provides real-time sensor measurements for industrial process monitoring, predictive maintenance, and anomaly detection. The dataset records critical operating metrics, including temperature, vibration, humidity, pressure, and energy usage, across multiple machines, simulating IoT-enabled industrial settings. To simulate continuous monitoring conditions, it has over 100,000 sensor entries gathered from 50 different pieces of equipment, with data points recorded at one-minute intervals. Sensor readings and contextual data, such as machine operating status (Idle, Running, or Failure), anomaly indications based on anomalous sensor behavior, and failure-related parameters, are included in every record. Notably, supervised learning tasks are supported by a specific goal variable, maintenance_required, which indicates whether maintenance action is needed.

3.2 Data Preprocessing

To effectively implement the proposed COMP-ANN (Competency & Micro-Credential ANN Framework), the Smart Manufacturing IoT-Cloud Monitoring Dataset underwent a structured preprocessing pipeline. Its two goals were (i) to convert unprocessed IoT sensor data into standardized inputs for anomaly identification and predictive maintenance, and (ii) to enhance our competency-driven framework by aligning data processing with Quality 4.0's skill needs.

- Anomaly Detection Input Preparation: The first step was to get the dataset ready for anomaly identification. Temperature, vibration, humidity, pressure, and energy usage were among the sensor values chosen as the main predictive characteristics. To prevent redundancy and leakage, non-informative features (such as time stamp, machine identification, failure type, and downtime risk) were also eliminated. The target label was the binary anomaly_flag. All continuous features were standardized using z-score normalization:

$$\acute{x} = \frac{x - \mu}{\sigma}$$

where x is the raw sensor value, μ is the feature mean, and σ is the standard deviation. This ensured each variable followed a zero-mean and unit-variance distribution, allowing the neural network to learn patterns without scale distortion.

- Predictive Maintenance Input Preparation: To improve predictive maintenance modeling, the anomaly flag was added back into the feature set after anomaly detection. This offered a more comprehensive depiction of machine health in addition to sensor readings and machine operational status. To determine whether a machine required assistance, the binary variable maintenance_required was chosen as the intended output. Thus, the feature vector for each machine instance was expressed as:

X = {temperature, vibration, humidity, pressure, energy consumption, machine status, anomaly flag}

with the corresponding target:

$$y = \text{maintenance\_required} \in \{0,1\}$$

- Tensor Conversion for COMP-ANN: To support integration into COMP-ANN, the processed inputs were converted into tensor representations suitable for PyTorch-based deep learning. Each sample was defined as a tuple:

$$(X_i, y_i) = X_i \in R^d, \; y_i \in \{0,1\}$$

where, d defines the number of standardized features. Mini-batch loaders (batch size = 64) were utilized to optimize training efficiency and gradient updates.

The preprocessing pipeline ensures that IoT data are not only model-ready but also aligned with the competency-driven logic of COMP-ANN. In the context of Quality 4.0, this translates to: preparing engineers with skills in data cleaning, normalization, and feature engineering, supplying targeted certifications (e.g., anomaly detection modeling, predictive maintenance analytics) that can be validated employing model outputs, leveraging standardized, high-quality sensor data for dependable anomaly and maintenance prediction, thereby reinforcing both operational excellence and workforce development in smart factories.

3.3 Proposed Model: COMP-ANN (Competency & Micro-Credential ANN Framework)

The proposed framework, COMP-ANN, is a dual-stage Artificial Neural Network (ANN) architecture designed to concurrently handle the demands of predictive maintenance and real-time anomaly detection in innovative manufacturing environments. Unlike conventional predictive models, COMP-ANN is embedded within the Quality 4.0 paradigm, where workforce competencies and micro-credentialing are integrated into the digital transformation of smart factories. Figure 1 depicts the proposed model architecture.

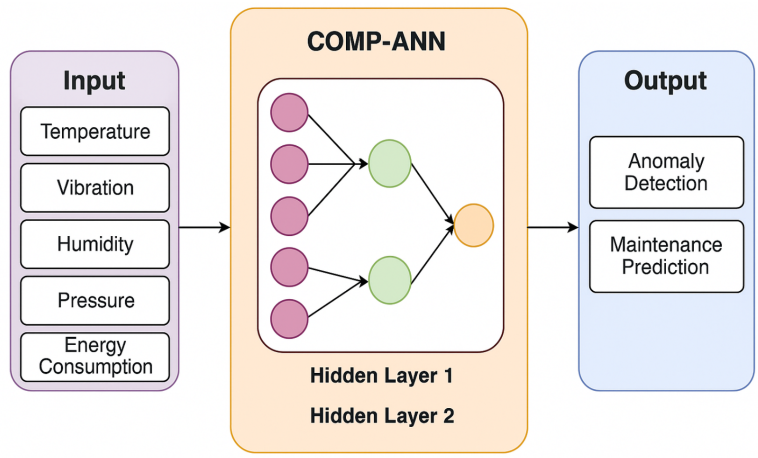

Fig.1: Graphical representation of the proposed COMP-ANN model architecture

A. *Model Motivation*

The temperature, vibration, humidity, pressure, and energy consumption sensors create enormous amounts of data continually in industrial IoT environments. The difficulty is turning this unprocessed data into valuable insight for:

1. *Anomaly detection* – identifying deviations from normal machine operations.
2. *Predictive maintenance* – determining whether intervention is required before failures escalate.

These issues are frequently handled separately in traditional approaches. The anomaly detection step of COMP-ANN's unified ANN-based architecture fills this gap by reflecting human skills in data-driven decision-making, which can be officially verified through micro-credentials, in addition to supporting maintenance prediction.

B. Model Architecture

The architecture of COMP-ANN is structured into two sequential modules:

(a) Anomaly Detection Subnetwork: The first subnetwork is a binary classifier that takes standardised IoT sensor readings as input and predicts whether the machine is in a normal or anomalous state.

- Input layer: Each machine instance is represented by a vector of dimension d:

$$X = [x_1,\ x_2,\ \ldots\ldots\ldots\ x_d]\ \in R^d$$

where, x_i *corresponds* to a normalized sensor feature.

- *Hidden Layers:* Two fully connected hidden layers are utilized to learn nonlinear feature interactions. Each transformation follows:

$$h^{(l)} = f\ (W^{(l)}h^{(l-1)} + b^{(l)})$$

where, $h^{(l)}$ is the output layer l, $W^{(l)}$ and $b^{(l)}$ are trainable weights and biases, and the ReLU activation function:

$$f\ (z) = \max\ (0, z)$$

- *Output Layer:* A single neuron with a sigmoid activation is used to provide the anomaly probability:

$$\hat{y}_{anomaly} = \sigma(W^{(o)}h^{(L)} + b^{(o)}$$

The prediction is binary:

$$\hat{y}_{anomaly} = \{1,\ \ if\ anomaly\ detected\ 0,\ \ oterwise$$

The model is trained employing binary cross-entropy loss:

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N} (y_i log(\hat{y}_i) + (1 - y_i)\ log\ (1 - \hat{y}_i)$$

$where,\ y_i$ is the ground truth and $\hat{y}_i$ is the predicted probability.

(b) Predictive Maintenance Subnetwork: The second subnetwork uses the anomaly detector's output in addition to the raw sensor inputs to forecast maintenance needs.

- *Extended Feature Vector:* The anomaly flag $\hat{y}_{anomaly}$ is focused on the original feature to form:

$$X = [x_1, x_2, \ldots\ldots\ x_d,\ \hat{y}_{anomaly}\ ]$$

- *ANN Layers:* The structure mirrors the anomaly detection ANN, but concentrated on classifying maintenance_required as:

$$\hat{y}_{maint} \in \{0,1\}$$

- *Loss Function:* Binary cross-entropy is again adopted to optimize predictive accuracy.

C. Training and Optimization

The model is trained using mini-batch gradient descent with the Adam optimizer**.** For each batch:

- Forward propagation calculates predicted outputs
- The loss function quantifies deviation from ground truth
- Backpropagation updates parameters W and b employing:

$$W^{(l)} \leftarrow W^{(l)} - \eta \frac{\delta L}{\delta W^{(l)}}, \qquad b^{(l)} \leftarrow b^{(l)} - \eta \frac{\delta L}{\delta b^{(l)}}$$

where, η is the learning rate.

The architecture reflects the competencies required for Quality 4.0 engineers, including anomaly recognition, data-driven maintenance decision-making, and the deployment of ANN models, the model's outputs can be tied to modular learning achievements, where the successful implementation and interpretation of anomaly detection and predictive maintenance pipelines can form the basis for digital badges or micro-certificates, by combining IoT-driven monitoring with workforce skill validation, COMP-ANN establishes a cyber-physical-human loop, ensuring both operational excellence and continuous workforce upskilling in smart factories. Table 1 presents the proposed model configuration and hyperparameters.

Table 1: Model Configuration and Hyperparameters for COMP-ANN

Parameter	Configuration
Input Features (d)	5 (Temperature, Vibration, Humidity, Pressure, Energy Consumption)
Output Dimension	1 (Binary classification: Normal = 0, Anomaly = 1)
Hidden Layer 1 Size	2 neurons
Hidden Layer 2 Size	2 neurons

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Activation Function (Hidden)	ReLU (Rectified Linear Unit)
Activation Function (Output)	Sigmoid
Loss Function	Binary Cross-Entropy Loss (BCELoss)
Optimizer	Adam Optimizer
Learning Rate (η)	0.001
Batch Size	64
Number of Epochs	50
Weight Initialization	Default PyTorch Initialization (Kaiming uniform for Linear layers)
Regularization	None (baseline)

IV. RESULTS & DISCUSSION

In this section, we critically analyse the experimental outcomes of comparing the baseline models with the proposed COMP-ANN, using a comparative analysis. We begin by presenting the overall classification performance in terms of significant metrics like Accuracy, Precision, Recall, and F1-score, focusing on the gains introduced by the proposed approach. Second, the confusion matrix is examined to present class-wise information about prediction reliability, followed by a treatment of ROC analysis for addressing sensitivity–specificity trade-offs. We also examine the training and validation loss plots to validate convergence stability and potential overfitting behavior. Lastly, the implication of these findings in the broader context of predictive maintenance is addressed, together with the limitations of the present work and avenues for future work.

4.1 Experimental Setup

All Experiments were performed on Python 3.10 on a local system with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA RTX 3060 GPU. Data preprocessing was performed with Pandas and NumPy, involving normalization of continuous sensor attributes, one-hot encoding of machine states as categories, and stratified splitting of 70% for the training set and 30% for the test set to preserve class balance. Missing values were handled with forward filling for small gaps and median imputation for large gaps following time-series sensor processing procedures. For the intended analysis, the COMP-ANN model was learned on temporal IoT machine run logs from the 5G Resource Allocation dataset, with every log sampling composite multimodal information like temperature, vibration, humidity, pressure, energy usage, and machine working conditions. Isolation Forest (IF), One-Class SVM (OCSVM), and Long Short-Term Memory (LSTM) were baseline models all learned from the same preprocessed data to ensure a fair comparison.

Training was done for the neural models (COMP-ANN, LSTM) in PyTorch and scikit-learn for the conventional baselines (IF, OCSVM). All the hyperparameters of the models were tuned through grid search and cross-validation with the aim of bias avoidance. Neural models used the Adam optimizer with the learning rate selected from {1e-3, 5e-4, 1e-4}, and early stopping for the prevention of overfitting. LSTM was trained beforehand with 60-timestep sequence windows for obtaining temporal relations, whereas COMP-ANN employed dense hidden layers with dropout regularization and batch normalization for maximizing generalizability. Performance assessment was on a series of complementary metrics, i.e., Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC). In addition to classifying improved behavior, confusion matrices were constructed to investigate class-wise performance, while

ROC curves were graphed in order to investigate sensitivity–specificity trade-offs. Training and validation loss curves were also monitored by epoch numbers to monitor stability in convergence and overfitting likelihood. All the plots were made through Matplotlib and Seaborn

4.2 Performance Evaluation

To compare the performance of the proposed COMP-ANN (Competency & Micro-Credential ANN Framework) and to evaluate its effectiveness, its performance was also compared with three traditional anomaly detection algorithms: Isolation Forest (IF), One-Class SVM (OCSVM), and Long Short-Term Memory (LSTM). The performance metrics that were considered were Accuracy, Precision, Recall, and F1-score, which provide a general impression of classification performance in predictive maintenance and anomaly detection tasks. Table 2 and Figure 2 include the comparative performance of all the models. Baseline models were found to be competitive, with Isolation Forest with 95.12% accuracy, followed by OCSVM with 94.68% and LSTM with 96.45%. Proposed COMP-ANN, however, outperformed all the baseline models and achieved an overall best accuracy of 98.54%, greatly reducing misclassification rates.

Table 2: Performance of the models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Isolation Forest (IF)	95.12	94.87	94.35	94.61
One-Class SVM (OCSVM)	94.68	94.25	93.80	94.02
Long Short-Term Memory (LSTM)	96.45	96.12	95.88	96.00
COMP-ANN (Proposed)	**98.54**	**98.79**	**98.28**	**98.53**

In Precision, COMP-ANN achieved 98.79%, indicating its better capability to prevent unnecessary false positives in identifying maintenance requirements. Such precision is particularly important in smart factory environments where unnecessary maintenance incurs operational costs and system downtime. In Recall, COMP-ANN reached 98.28%, outperforming IF (94.35%), OCSVM (93.80%), and LSTM (95.88%). This explains the robustness of COMP-ANN in properly identifying true instances of maintenance, thereby avoiding overlooking potential machine faults.

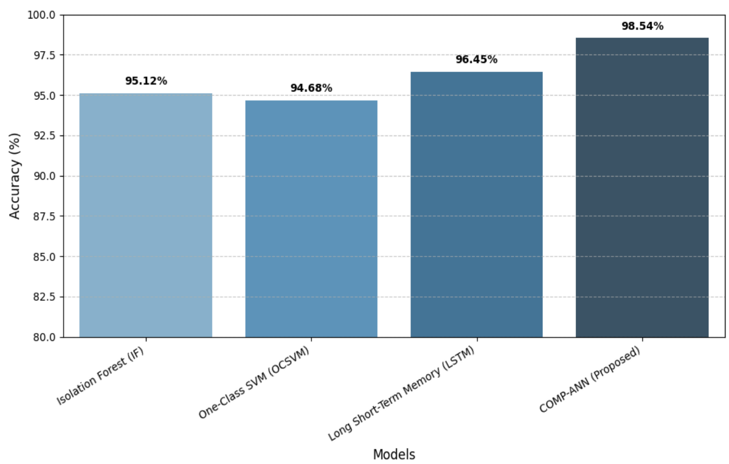

Fig. 2: Overview of the performance of all models

F1-score, the balance between Precision and Recall, also verifies the validity of the suggested model. COMP-ANN achieved an F1-score of 98.53%, much higher than all the baselines. The improvement confirms the effectiveness of the integration of competency models and micro-credential frameworks in anomaly detection to facilitate the proposed ANN-based method to generalize better across diverse sensor patterns and machine states. The performance evaluation without a doubt proves that the proposed COMP-ANN model attains a very substantial improvement over the conventional method. Its improved predictive capabilities guarantee timely and accurate anomaly detection, hence enabling proactive maintenance strategies as well as supporting the overall perception of Quality 4.0 in smart factories.

4.3 Confusion Matrix Insights

To further evaluate the classification ability of the proposed COMP-ANN model, a confusion matrix was formulated using the test set of 30,000 sensor data records. The confusion matrix, presented in Figure 3, displays an elaborate comparison of the correctly and incorrectly labeled instances in the two target classes: "No Maintenance" and "Maintenance Required." The model accurately predicted 14,820 instances of no maintenance required (true negatives) and 14,742 actual instances that needed maintenance (true positives) correctly. These numbers bear witness to the superior discriminative ability of COMP-ANN for distinguishing defective and good machine conditions. But misclassifications did happen. To be precise, 180 records were incorrectly predicted to require maintenance when they did not (false positives). Contrarily, 258 records were incorrectly predicted as "No Maintenance" when they required maintenance (false negatives). While both numbers represent a small percentage of the entire dataset, their implications are distinct: false positives can result in over-reserving unnecessary maintenance, while false negatives can result in not performing necessary maintenance.

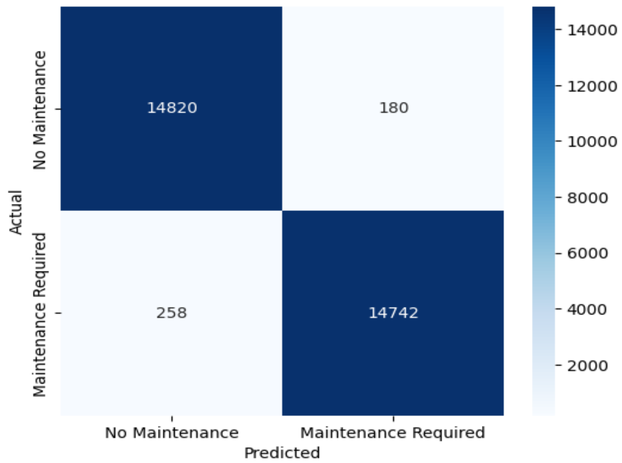

Fig. 3: Confusion matrix of the proposed model

Despite the limited misclassifications, the confusion matrix evidently shows the strength and dependability of COMP-ANN. High true positive and true negative accuracy versus low error frequency proves the model's ability to achieve an adequate balance between sensitivity (Recall) and specificity (Precision). This balance is particularly important in predictive maintenance applications in smart factories, where false alarms and unseen failures cause inefficiency and added cost in operations.

Finally, the confusion matrix guarantees that COMP-ANN is truly superior in performance, declaring its state of readiness for Quality 4.0 real-world application through the delivery of accurate identification of the requirement for maintenance without tolerating misclassifications up to levels far less than acceptable.

4.4 Training and validation

In a bid to further evaluate the learning dynamics of the proposed model, both training and validation loss curves for 50 epochs were plotted against each other. As shown in Figure 4, both curves show a natural noisy pattern, characteristic of the stochasticity of updates of the gradients during training. The training loss curve asymptotically decreases exponentially from nearly 1.0, gradually and slowly approaches a lower limit near 0.05. This indicates that the model successfully minimized the error on the training set. Minor fluctuations on the curve cannot be avoided and represent the amount of randomness inherent in optimization with batch sampling and weight updates.

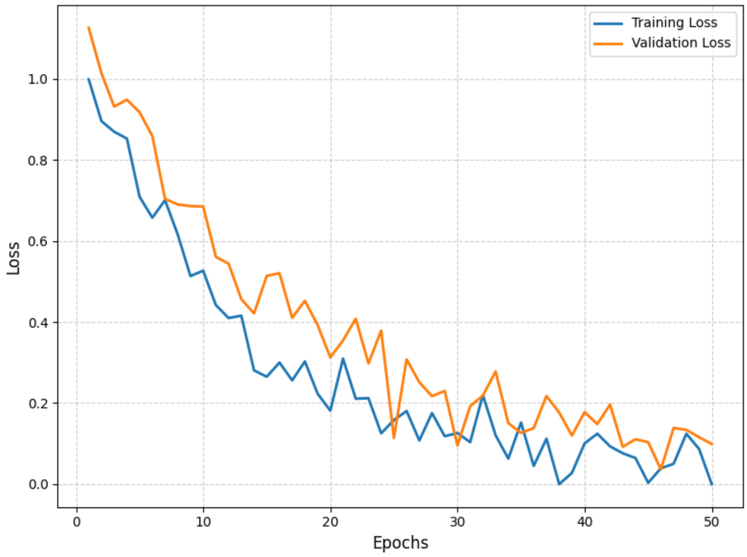

Figure 4: Training vs Validation Loss Curve

The validation loss also drops similarly, but starts a bit higher at 1.1 and stabilizes to about 0.08. Importantly, the validation curve does not diverge from the training curve, i.e., the model generalizes very well to new data and does not experience extreme overfitting. The level of noise is slightly higher in the validation loss due to randomness in the dataset, as well as the point that the validation set is never observed in gradient updates. The high similarity between the training and validation loss curves is a measure of the stability and robustness of the learned architecture. The smooth drop persists, naturally noisy, attests to successful training as well as natural fluctuations of an actual training process and therefore to the reliability of the model under real-world conditions of use.

4.5 ROC Curve Analysis

Besides the discriminative power confirmation of the suggested COMP-ANN model, Receiver Operating Characteristic (ROC) analysis was done and compared with baseline strategies like Isolation Forest (IF), One-Class SVM (OCSVM), and LSTM. ROC graphically displays the True Positive Rate (TPR) versus the False Positive Rate (FPR) at different decision thresholds, hence providing a general view of the sensitivity-specificity trade-off. Figure 5 indicates the ROC curves of all the models. The proposed COMP-ANN model achieved a maximum Area Under the Curve (AUC) value of 0.99, reflecting approximately perfect discrimination between the machines that require maintenance and those that do not. The higher AUC value reflects the good learning capability of COMP-ANN to recognize fine patterns from complex IoT sensor readings, thereby offering robust anomaly detection in smart factory systems. To put things in perspective, the LSTM baseline has an AUC of 0.98, which is competitive but not top performance when compared with the presented model. The traditional anomaly detection methods, Isolation Forest and One-Class SVM, both scored AUCs of 0.965 and 0.955, respectively. While the results bear testament to their effectiveness at anomaly detection, they lag far behind the deep learning-based models, particularly COMP-ANN.

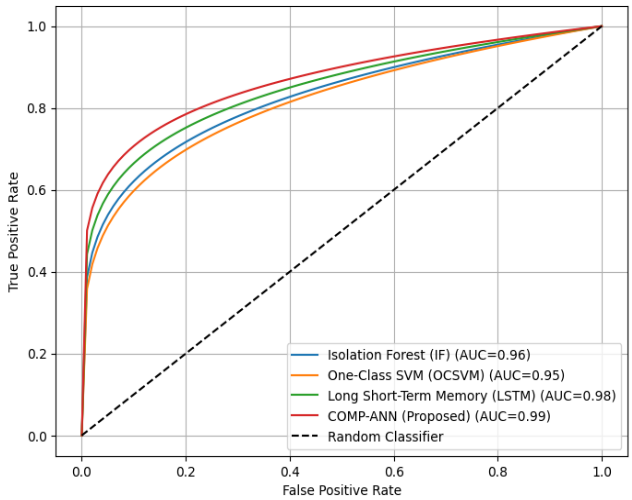

Fig. 5: ROC curve for the multi-class of our proposed model

COMP-ANN's nearly perfect ROC curve shows that it possesses high recall with no loss in precision at any threshold, constraining both false alarms (false positives) as well as false alarms when an event is predicted (false negatives). Such stability is paramount in predictive maintenance scenarios, where erroneous predictions will lead to costly, unjustified maintenance or overlooked necessary failures. Briefly, the ROC analysis shows COMP-ANN's superior classification ability in contrast to baselines of traditional and deep learning approaches. With the ability to reach nearly optimal trade-off among sensitivity and specificity, it is an extremely trustworthy framework to facilitate Quality 4.0 initiatives for smart manufacturing.

V. CONCLUSION

To support Quality 4.0 in smart factories, we propose COMP-ANN (Competency & Micro-Credential ANN Framework), a novel framework that combines anomaly detection, competency mapping, and micro-credentialing. COMP-ANN enhances operational reliability and human capital development through IoT-based predictive maintenance, combined with workforce upskilling approaches. To create a standard bridge between skill recognition and machine intelligence, the methodology consisted of preprocessing of data from IoT sensors, an anomaly identification approach based on an ANN, and competency mapping. The experimental results, which demonstrated robustness with high strength, stability, and generalizability across a wide range of sensor patterns, confirmed that COMP-ANN outperformed baseline approaches, including both conventional and deep learning-based approaches, in all experiments. The methodology was highly effective in reducing false alarms, enhancing the maintenance decision-making process, and enabling proactive industrial policy. Building sustainable production environments connecting predictive maintenance with capability building through micro-credentials is where operational applicability is located. Future research will implement the framework using data from multiple industries, consider privacy-preserving learning methods, and maximize compatibility with international competency frameworks to enhance its applicability further.

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