Improving Product Quality Control in Smart Manufacturing through Transfer Learning-Based Fault Detection

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***Abstract*—Reducing product failure rates is crucial to ensure a healthy production line. However, the current approach for inspecting product quality is inefficient, costly, and time-consuming, relying on manual inspection at the end of the production process. This research paper focuses on the utilization of transfer learning, an intelligent machine-learning technique, to improve the accuracy and efficiency of product quality inspection in production lines. The proposed approach utilizes transfer learning to adapt a pre-trained model from a related domain to the target domain, enabling accurate product quality prediction with limited data. The reference architecture provides a framework for implementing the proposed approach in a manufacturing environment, enabling real-time monitoring and decision-making based on product quality predictions. The proposed approach can improve the accuracy of faulty product detection by up to 11% compared to traditional techniques, as demonstrated by evaluations on a real-world production dataset.**

***Index Terms*—Smart Manufacturing, Industry 4.0, Product Fault Detection, Transfer Learning**

I. Introduction

Maintaining a good quality product production is crucial to minimize the occurrence of defective products and make sure of low failure rate. Defective products can cause significant economic losses for the manufacturing industry businesses as they are not being sold or used in the further stages of the production system. In addition, a high quantity of faulty products can result in wastage and unnecessary energy consumption since defective items are often discarded as waste materials. Given our growing dependence on industrial goods, addressing this issue is crucial for achieving both economic and environmental sustainability [1]–[3].

The effective management of production lines requires an efficient quality control strategy, as different methods used to inspect product quality are less efficient, expensive, and time-consuming [4]. Although data-driven machine learning (ML) and Deep Learning (DL) techniques [5] have demonstrated efficacy in detecting faulty products, they face challenges such as limited availability of labeled faulty product data and discrepancies in data distributions between source and target domains [6]. Fortunately, Transfer Learning (TL) offers a solution to these issues. Recent research has established that TL can surmount target domain inadequacies in training datasets by utilizing knowledge acquired from relevant source domains [7]. Moreover, TL can substantially reduce the computational resources and time required to train a model by leveraging pre-existing knowledge from various domains.

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TL has been successful in improving fault detection accuracy in different domains indicating its effectiveness in industrial settings. Thus this paper proposes a TL-based solution for detecting faulty products in smart manufacturing that leverages pre-learned knowledge from related domains. The proposed approach can improve model performance and reduce the cost and time required to train a model from scratch on a limited amount of labeled faulty product data. Thus, proposed TL-based approach has the potential to enhance the accuracy and efficiency of quality control, leading to a reduction in economic losses and environmental waste. It can be implemented in various industrial settings as a low-cost and efficient solution for detecting faulty products.

II. Methodology

The proposed solution for faulty product detection in smart manufacturing employs transfer learning to enhance the performance of deep learning models by leveraging knowledge from related domains. Fig. 1 illustrates the detailed TL based model used in the proposed approach for faulty product diagnosis. In the proposed approach initially an ancestor model A_m is trained on any of the publically available dataset. Now with TL the ancestor model A_m is concatenated with CNN Model C_m to produce hereditary model H_m. Further the hereditary model H_m is used to detect the faulty product in the production line of the manufacturing system. The major steps involved in the proposed approach consist of preprocessing and feature selection, ancestor model building for TL, and hereditary model building with fine tuning.

A. Pre-processing and feature selection

Data pre-processing is crucial for data analysis, involving cleaning, transforming, and organizing data. In this work preprocessing involves handling NULL and NaN values through zero imputation, scaling data, and employing feature selection using ANOVA techniques (reducing the number of features from 591 to 15) to improve dataset quality and reduce training time, CPU and memory utilization, while increasing prediction accuracy.

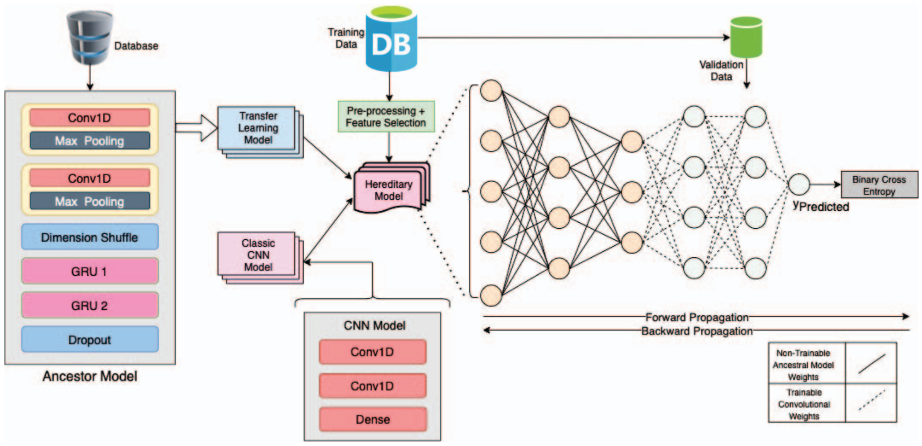

Fig. 1. Proposed model architecture with transfer learning

B. Ancestor model building for TL

The ancestor model is a pre-trained model which is typically trained on a large dataset for a particular task. Transfer learning attempts to apply the knowledge acquired from a previously learned model A'_m to a new, new model H'_m. By transferring the parameters from a pre-trained ancestor model, transfer learning can assist in training a target model by initializing it with relevant knowledge. Rather than training a new model from scratch for a different task, transfer learning involves taking the pre-trained model and fine-tuning it with a smaller dataset specific to the new task. The pre-trained model helps in new model training with learned useful features that can be applied to the new data. This can result in faster training times and better performance on the new task.

The ancestor model is build using a combination of CNN and GRU, where CNN consists of two convolution layers and two GRU layers along with pooling, dimension shuffle, and dropout layers as shown in Fig. 1.

This transferable property of transfer learning could be utilized to develop anomaly detection models which have some pre-trained knowledge of anomaly detection. It works as an experienced model which transfer its anomaly detection strategic knowledge (weights) to its children (the new model being built from it)

C. Hereditical model building and fine-tuning

In this phase, we perform fine-tuning on a pre-trained ancestor model. Firstly, we remove the bottom layer of the ancestor model and append an output layer. The weights of the newly added output layer are initialized randomly. Subsequently, we set the layers of the ancestor model as untrainable and introduce two CNN layers, along with a Dense layer serving as the output. Throughout the training process, the earlier layers of the model are kept frozen while the trainable layers' weights are updated to minimize the discrepancy between predicted and true labels. Once the model has been trained for a sufficient number of epochs, it is fine-tuned, and the deep architecture, along with all of its parameters, is stored for future applications.

III. Experimental Evalaution

Python 3.0 is used to develop and analyze the proposed mechanism on a MacBook Pro with an Apple M1 Pro processor, which has a 10 core CPU, 16 core GPU, 16 GB of RAM, and a 1TB SSD. To evaluate the proposed approach a publically available semiconductor dataset SECOM [8] is used, which consists of 1567 samples with 590 manufacturing operation variables and single quality variable. We used 30% of the dataset for transfer learning and from remaining dataset 70-30 train test split with cross validation is used for the model evaluation.

Table I shows the results obtained for different algorithms on the testing dataset. The proposed method, which is based on Transfer Learning with a Convolutional Neural Network (TL+CNN), achieved the highest accuracy of 98.76%. The execution time for the proposed method was also reasonable, with a value of 4.14 seconds. Among the other methods, such as Multilayer Perceptron (MLP), Gated Recurrent Unit (GRU), and Long-Short Term Memory (LSTM), TL+MLP achieved the next highest accuracy of 96.14%, with an execution time of 4.09 seconds. TL+GRU and TL+LSTM achieved the same accuracy of 95.03%, with execution times of 6.99 and 6.89 seconds, respectively. These results demonstrate the effectiveness of the proposed TL+CNN approach in accurately detecting faulty products in smart manufacturing while maintaining a reasonable execution time.

TABLE I
Comparison of DL models with transfer learning

Algorithm	Accuracy	Execution Time
TL+MLP	96.14	4.09
TL+GRU	95.03	6.99
TL+LSTM	95.03	6.89
Proposed (TL+CNN)	**98.76**	**4.14**

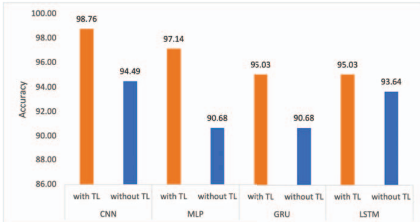

Fig. 2. Comparison of proposed model with DL techniques with and without TL

Fig. 2 provides the results of the experiments conducted to evaluate the impact of transfer learning (TL) on the accuracy of different models. The accuracy of each model is reported with and without the use of TL. The MLP, GRU, LSTM, and CNN models are evaluated.

When TL is used, the MLP model achieves an accuracy of 97.14%, which is significantly higher than the accuracy achieved without TL, which is 90.68%. The GRU and LSTM models also show an improvement in accuracy when TL is used, achieving accuracies of 95.03% and 95.03%, respectively.

The CNN model shows the highest accuracy of all the models, achieving an accuracy of 98.76% with TL, compared to an accuracy of 94.49% without TL. These results suggest that TL has a significant impact on the accuracy of the models, particularly the CNN model, and can be an effective technique to improve model performance.

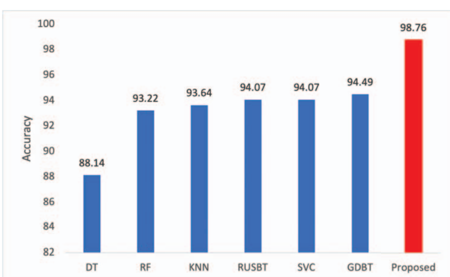

Fig. 3. Comparison of proposed model with ML techniques

The proposed model is also compared with different ML techniques. Fig. 3 shows the comparison of the proposed model (TL+CNN) with traditional machine learning techniques in terms of their testing accuracy. The proposed model achieved the highest accuracy of 98.76%, followed by the Gradient Boosting (GDBT) with an accuracy of 94.49%. The remaining ML techniques, including Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Random Under Sampling Boosted Tree (RUSBT) and Support Vector Classifier (SVC), achieved lower accuracies ranging from 88.14% to 94.07%. Overall, the proposed model outperformed all traditional ML techniques, demonstrating the effectiveness of the transfer learning approach in improving the accuracy of the faulty product detection system.

IV. Conclusion and Future Work

This work proposes the utilization of transfer learning to improve the accuracy and efficiency of product quality inspection in manufacturing environments. By adapting a pre-trained model from a related domain to the target domain, the proposed approach enables accurate product quality prediction with limited data. Evaluations on a real-world production dataset demonstrate that the proposed approach can improve the faulty product detection accuracy up to 11% compared to traditional techniques.

In our future work, we plan to extend the mentioned transfer learning based solution for product fault detection in the form of micro-service. Moreover, we intend to provide various transfer learning models in the form of APIs to evaluate the performance of the models accurately and choose the appropriate model as per the available dataset. This will enable users to choose the best transfer learning model based on their specific requirements. Using simple API calls user can select method of his choice within each service and customize its own procedure for the detection of faulty products. Our research to have an impact, manufacturing industry can use the proposed approach in a self-adaptive system, and any automated agent in the system can use it, try different combinations, identify the optimal one, and use it for predictions. This overcomes the dependency on ML expert to build the ML models for the detection and classification of faulty products in the manufacturing domain.

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References

[1] Y. H. Chun, "Improved method of estimating the product quality after multiple inspections," *International Journal of Production Research*, vol. 54, no. 19, pp. 5686–5696, 2016.

[2] S. Kang, E. Kim, J. Shim, W. Chang, and S. Cho, "Product failure prediction with missing data," *International Journal of Production Research*, vol. 56, no. 14, pp. 4849–4859, 2018.

[3] C.-C. Yang, "Improving the definition and quantification of quality costs," *Total Quality Management*, vol. 19, no. 3, pp. 175–191, 2008.

[4] T. P. Carvalho, F. A. Soares, R. Vita, R. d. P. Francisco, J. P. Basto, and S. G. Alcalá, "A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering*, vol. 137, p. 106024, 2019.

[5] P. Verma, J. G. Breslin, and D. O'Shea, "Fldid: Federated learning enabled deep intrusion detection in smart manufacturing industries," *Sensors*, vol. 22, no. 22, p. 8974, 2022.

[6] T. Zonta, C. A. Da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li, "Predictive maintenance in the industry 4.0: A systematic literature review," *Computers & Industrial Engineering*, vol. 150, p. 106889, 2020.

[7] S. Niu, Y. Liu, J. Wang, and H. Song, "A decade survey of transfer learning (2010–2020)," *IEEE Transactions on Artificial Intelligence*, vol. 1, no. 2, pp. 151–166, 2020.

[8] M. McCann and A. Johnston, "Secom dataset uci machine learning repository," 2008.