Optimizing Industrial Engineering Performance with Fuzzy CNN Framework for Efficiency and Productivity

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***Abstract*—In industrial engineering, efficiency is paramount. Convolutional Neural Networks (CNNs) are commonly used to identify and detect labour activity in industrial environments. Accurate fault detection is crucial for identifying and classifying defects in production. This research proposes a novel approach to enhancing industrial performance by predicting defects in manufacturing processes using a fuzzy-based CNN technique. The framework integrates cutting-edge fuzzy logic with CNNs, improving diagnostic model efficacy through fuzzy logic-based weight adjustments during training. Additionally, a novel fuzzy classification method is used for defect detection, followed by a demand forecast error simulation tailored to specific regions. The framework begins with initial training data, which is then combined with multiple classifiers to form a comprehensive dataset. The CNN, enhanced by fuzzy logic for weight updates, first employs fuzzy classification to diagnose errors, then simulates demand forecast errors regionally. This refined dataset is subsequently used as input for the CNN. Implementation in a manufacturing organization demonstrates the proposed framework's effectiveness, significantly improving fault diagnostic accuracy compared to traditional methods. By leveraging the latest advances in CNNs and fuzzy logic, the framework offers a robust solution for boosting industrial efficiency. This comprehensive approach to defect detection in industrial processes seamlessly integrates CNNs with fuzzy logic, highlighting the framework's utility and potential impact on industrial efficiency. The results underscore the viability of this innovative technology in enhancing industrial engineering performance.**

Keywords*—Industrial Engineering performance; manufacturing industry; fuzzy-based convolutional neural network; fault diagnostic

I. Introduction

Higher reliability, protection, and accessibility in real-world mechanical systems are in high demand owing to the current manufacturing sector's fast evolution. Modern industry relies on machine fault diagnostics and health prediction to cut down on pointless regular maintenance, increase security, and boost the dependability of manufacturing equipment. Conventional framework for diagnostics for defect diagnostics, and typically combine cutting-edge signal processing tools and machine learning strategies. In this framework, the automated edge detection and selection processes are crucial. Currently, there is a strong desire among industrial engineers to develop ways to enhance operating efficiency, which should increase the number of initiatives that are finished on schedule, within the intended budget, and with the required scope. Only the most successful organisations can stand the test of time because of the recent economic slump. Companies that manage multiple projects at once need to know what steps to take to improve the productivity of their operations in a multi-project context. Practical implementations, however, show a significant knowledge gap regarding how to effectively improve the efficiency of the economy [1].

The study of the design, analysis, and management of systems, from small organisations to lone units of equipment, falls under the umbrella of industrial engineering. Industrial engineers work in a variety of sectors, including manufacturing, services, and the processing of raw resources. The most efficient way to use resources like people, equipment, substances, technology, and power to produce a good or deliver a service is determined by industrial engineers. Manufacturing is a significant component of industrial engineering. Operations researchers collaborate on the science behind some of these techniques; they create new methodologies, generate fresh optimization methods, and develop tools for analysing systems. Industrial engineers use computation, decision-making tools, graph theoretical methodologies, optimization algorithms, and software to solve problems [2] [3].

Systems with computational intelligence are essential for addressing complicated, real-world issues in the industrial sector [4]. One or more computer vision techniques, such as neural networks, fuzzy logic, evolutionary computation, multiagent strategies, and rule-based systems, are used by computational systems. To tackle a problem, it might also be required to use a hybrid system that combines different approaches. Fuzzy neural networks are a very effective hybrid tool because they combine the benefits of neural networks and FL. Because they employ fuzzy inference that is human-like, they are thought to be intrinsically more intelligible and allow the machine to incorporate expert knowledge.

Fuzzy logic systems have been extensively used in a variety of industrial applications, including autonomous railway operating systems, robot arm control, water quality monitoring, and car speed regulation. The system can be made more effective by using fuzzy logic. The Universal Approximation Theorem asserts that a fuzzy logic system may consistently estimate any non - linear function to any level of specificity, despite the fact that fuzzy logic is often thought of as a method for providing incorrect and ambiguous information. Fuzzy set theory is used by the fuzzy estimation system to map inputs to outputs. The Mamdani- and Sugeno-type fuzzy inference systems are widely used. A decision-making unit, a rule repository, a fuzzification interface, and a defuzzification interface make up a fuzzy-inference system [5].

Fuzzy logic methods perform remarkably well in extremely complex and nonlinear processes, as well as when no straightforward mathematical proof is readily available. In the process of electric discharge machining, a novel pulse discriminator is created using fuzzy logic techniques. Reducing effectiveness indices used in the electro-discharge machining process, such as component removal rate and surface quality, are directly related to the discharge pulses used in the process [6]. The fluid catalytic cracking unit is managed using fuzzy logic. The improved method of controlling the fluid presence of a catalyst in the refining production process is accomplished using fuzzy logic control as a control scheme.

Fuzzy systems are well suited to approximated inference, especially in organisations with a difficult-to-achieve quantitative design [7]. Theoretically, fuzzy sets can be viewed as both a huge problem and a way to solve it. The capability of fuzzy logic to display ambiguous facts is its fundamental feature. Systems that are challenging to precisely specify have been designed using fuzzy logic. Successful applications of fuzzy logic in industrial engineering have been documented recently. The fuzzy logic concept can be viewed as a useful tool for handling the variety of challenges that industrial engineers face when working with partial and uncertain data. When the fluctuations of the decision-making problem prevent a realistic assessment of the design variables, fuzzy logic provides an effective instrument to aid exploration in industrial engineering. Fuzzy neural networks (FNN) are an AI method created by combining fuzzy logic and neural networks. FNN uses a neural network approach to manipulate the fuzzy set and fuzzy regulation variables that make up a fuzzy system. When there is no mathematical proof for a specific issue, FNN is mostly used for pattern recognition, regression, and feature extraction methods [8].

The CNN, also known as the Feed Forward Neural Network Network, is a widely used type of ANN that uses convolution as an equivalent to matrix propagation in at least one of its regions. CNN is primarily employed for processing natural language economic time series data, and image/video identification and classification. "Local sparse interconnections between sequential information, weight sharing, and pooling" are the three fundamental principles used by CNN [9]. The first two factors are employed to cut down on the amount of adaptive algorithm, and pooling is employed to cut down on the size of the features. The hidden layers, which are in charge of sophisticatedly extracting features, and the classification layers, which are in charge of making decisions based on information gathered from previous levels, make up CNN.

Convolutional neural networks, used as a back-propagation algorithm model for DL, have made some major advancements and achieved snipping outcomes in a broad range of computer visual and information-processing tasks. Convolutional networks have also just been incorporated into the field of device defect diagnosis in the past five years. The purpose is to help investigators, professionals, and even beginners who want to use convolutional networks for fault diagnosis in comprehension and implementation by first teaching the theoretical foundations of CNN before looking at its applications. It has one final output, one hidden layer, numerous convolution-pool layers, many fully linked stages, and one facility available [10]. The structure of CNN incorporates two well-liked operations—batch normalisation and dropout—that are designed to enhance the quality of the model. Each function will be described in its section after that. The working process of CNN is explained in Fig. 1.

The remaining subsections are organised as follows: The related work is included in Section II. The suggested F-CNN strategy is discussed in Section III. The proposed method was put to the test for problem diagnosis in Section IV to improve performance, and the results were displayed in tables and graphs in Section V. Section VI provides the Conclusion.

II. RELATED WORKS

The paper [11] investigates the relationship between lean production and increased operating performance in Brazil to see how Industry 4.0 technologies can help improve industry performance in a growing economy. Since the emergence of Industry 4.0, businesses have focused their efforts on increasing degrees of automation and interconnectivity in order to attain higher performance. These technologies will eventually be incorporated into well-known and successful production methodologies like lean production, which could either improve or harm operating efficiency. The variables seemed to have a smaller impact than in earlier experiments. The authors highlight a number of alternatives for additional research in diverse socioeconomic circumstances. However, the paper provided concrete proof that adopting technology alone will not produce noteworthy outcomes. In order to design and operate manufacturers' processes in the period of the fourth industrial revolution, LP techniques encourage the establishment of organisational practises and attitudes that promote fundamental operational efficiencies.

The paper [12] plans to forecast a system of quantitative measures that makes it possible to monitor the achieved environmental policy of an IS network in industrial sites. To support the primary goal of IS development, With the use of a system of quantitative measures, the given guidance framework is intended to help IP participants in IS networks define environmental goals and monitor their progress over time. For extracting appropriate objective measurements for each of the three measurements (ecological, financial, and cultural), multifaceted renewable energy perceptions in the form of a complex mathematical implementation, specific, formed, and internationally standard methodologies—such as MSNA, LCA, MFA and — Flow Cost Accounting are used. The predictor network significantly contributes to the innovation context of IS networks once it is integrated into an information technology-assisted IS tool, supporting environmental paths. However, the prediction method needs more time for the enhancement.

In the paper [13], makes an effort to calculate, from a complexity perspective, how the emission reduction target legislation will affect industrial performance. The Chinese government has implemented a variety of mitigation actions to reduce CO2 emissions in an effort to combat global warming. The Chinese government established the emission reduction target strategy during the 11th Five-Year Plan with the goal of reducing energy usage per unit of gross domestic product by 20%. The findings indicate that less coal is consumed in industries with increased complexity. Reducing emissions target policies typically hurts the likelihood of starting new businesses and reduces a specific industry's profitability and productivity. For more complicated industries, however, this adverse effect is less pronounced. The performance of an industry can be improved by emission reduction target legislation rather than having a negative impact, but only in particularly complex industries. the paper not only contributes to the formulation of a more successful industrial development plan, but it also suggests a feasible path toward achieving both economic growth and greenhouse gas emission reduction simultaneously.

The paper [14] investigates if EI acts as a link crossing industry technology to better operational efficiency in underdeveloped countries. The usefulness of activities linked to EI may be strengthened or diminished by the implementation of Industry technology by manufacturing organizations within this socio - cultural context, changing the pace of enhanced organizational performance. The paper carried out a survey of 147 Brazilian companies that have already started integrating Industry 4.0 technology alongside current, largely dependent continuous quality improvement based on EI. Results indicate that there is a positive mediating role for the EI in the relationship between Industry 4.0 adoption and improved operational performance. The findings demonstrate that the development of Industry and the high-tech movement do not neglect the importance of worker autonomy and involvement. The principle remains true even in situations like advanced markets, where the health of the workforce may create extra obstacles for the introduction of Industry 4.0. Given implementing Industry appears to be a viable approach for assisting employees in continuous quality improvement and reinforcing the value of their consultation and participation, specifically in businesses in industries with advanced degrees of technical complexity.

The explosive growth rise in interest in the BDPA in the field on operations and industrial production administration served as the impetus for the paper [13]. Notwithstanding the attention including both researchers and practitioners, theory-based work on the function of BDPA in company's efficiency is still lacking. Oliver (1997) demanded that create a theoretical background relying on institution supposition and RBV to confront the limitations of the RBV and also used objective support to examine how the selection of resources, which is impacted by three organisational practises, can assist in the creation big data capabilities, which in essence can help to achieve process performance. The following are the limitations of the investigation. First off, despite receiving a lot of attention, contend that Ling Yee's observation that the RBV lacks context sensitivity is correct (2007). Additionally, take the lack of context sensitivity as a sign that RBV is incapable of recognising the circumstances in which assets or functionality can be most beneficial. However, the contingency theory that enhances the model is not used in the paper, so internal and external factors will affect manufacturing performance.

In the paper [15], machine learning techniques that can be used to create manufacturing mechanisms with adaptive behaviours are given as part of a thorough literature analysis. Additionally, it highlights several important research queries with the same goal that are left unaddressed in the most recent literature. The work seeks to give scholars a solid grasp of the primary strategies and algorithms employed over the past 20 years to enhance manufacturing operations. Planning, tracking, assurance, and failure are the four primary topics under which the earlier ML studies and more modern manufacturing innovations are grouped.

It covers every facet of current industrial solutions, including tasks (such as segmentation, categorization, and prediction), methods (such as SVM and neural networks), learning styles (such as ensemble methods and DL methods), and performance indicators (i.e., accuracy and mean error percentage). Additionally, a detailed explanation of the essential steps of the KDD method is provided for use in industrial applications. Additionally, various viewpoints on specific statistics about the current situation are provided. In the paper offers a summary of the literature on the most recent developments in ML and DM organizational forms for the manufacturing sector. Applications that are currently in use as well as appropriate methods to complete the desired task were found. A number of machine learning approaches, which include proper supervision (logistic regression), unorganized (grouping, ARM, SPM, intrusion detection), ensemble learning, and DL, are utilized to show the relevance in the industrial sector. The benefits of ML-based investigations in the commercial sphere are also discussed in this work. It also provides a good knowledge of the difficulties faced by machine learning with production processes and machinery.

In the paper [16] a novel method for resilient supplier selection that takes advantage of data analytics breakthroughs while eliminating two fundamental drawbacks, namely the requirement to foresee performance implications and calculate the probability of disruptions. The relative frequency of risk events that are too continuous and unpredictable to be effectively recognized, calculated, and anticipated presents one challenge in managing robust vendor portfolios using interruption risk estimations. The work focuses on using the benefits of electronic data in intelligent manufacturing systems to predict the provider tendency to interruptions and the accompanying influence on Organizational performances rather than predicting probability of extremely unpredictable events. Particular attention was paid to robust evaluation process in manufacturing technologies in the work. A platform for digital assemble production was used to run the testing period. The results show that the use of SML methods can help with a thorough selection of suppliers which will lead to more dependable supplier fulfilment and improvements in risk management decision-making. These limitations suggest a number of possible improvements for the work. Examples include differentiating supplier profiles, where a more reliable provider has higher costs, or varying quantities available at various suppliers, or pricing competition amongst suppliers.

The paper in [17] emphasizes mostly on AM metallic concepts designed for use as bone graft substitutes and orthopaedic purposes, and it examines the state of the art regarding the performance characteristics under quasi-static and dynamic load levels. The configuration relationships are investigated for typical beam-based grain structure; sheet-based structures, including all those founded on data entity regular lowest areas, and graded designs. Also covered are the computational and theoretical methods that were used to predict the topology-property links in the paper. This overview of the quasi-static material properties and exhaustion actions of AM met biomaterials also covers the significance of the AM methodologies, depending on the material, tissue repair, and enzymatic degradation, different surface bio-functionalization, post-manufacturing (thermal) operations, and loading components. AM meta-biomaterials (auxetic meta-biomaterials) are also covered in the session and exhibit unusual material properties such as improved mechanical properties, physical property activity, and poor Poisson's proportions (such movable devices). However, the technique can make things take more time.

To provide the circumstances for energising the social, ecological, and technological subsystems and stimulating advances in sustainable production performance, management support is necessary. Due to the fact that the segments do not sacrifice on growth or performance, the results are also acceptable for aggressive enterprises looking to maintain the competitiveness. Employees in production facilities benefit from high levels of engagement and involvement to pursue sustainable production projects thanks to strong levels of managerial support. Information also supports the idea that advanced sustainability initiatives are critical to improving industrial efficiency durability. The extent of managerial support and facilitation, however, determines how often environmental management approaches are used. The findings demonstrate that sustainable manufacturing practises and managerial support are mediated by environmental activities. Similar to this, technical work methods like TQM, TPM, and JIT mediate the link between management backing and successful sustainable production [18].

III. DATA COLLECTION

Juchao Information, Hexun Finance, the China Securities Industry Association, and the National Bureau of Statistics provided the majority of the data used in this study. Tiny target fault statistics from one operational environment and large source fault data from another operating condition make up the training samples. This test rig offers a useful and dependable testing environment for fault diagnosis and satisfies all controlling different for vibrations analyzers.

IV. METHODOLOGY

On the basis of transfer learning with a CNN, a novel method for diagnosing machinery faults is suggested. This approach is focused on solving the issue of the objective data's tiny samples instead of requiring the huge same-distribution samples demanded by other machine learning approaches. On the basis of the literature study, that productivity in industrial engineering is influenced by organization effectiveness improvements. Here the F-CNN is proposed to identify the fault to enhance the performance. In Fig. 1 flow diagram of recommended system has explained.

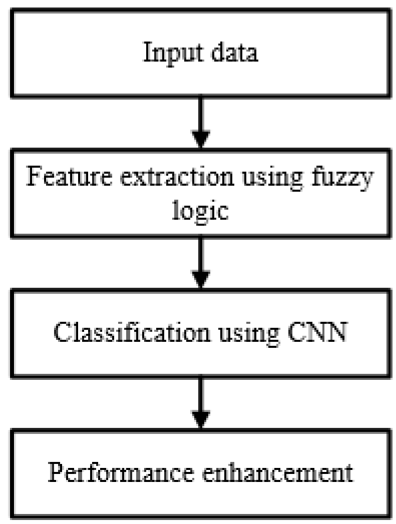

Fig. 1. Flowchart for suggested system.

A soft computing technique called fuzzy logic creates practical algorithms by incorporating structured human knowledge. It is a logical framework that presents a model created for inexact rather than precise human interpretation modes. The fuzzy logic system can be applied when creating intelligent systems that employ information that has been communicated in particular intelligence. Although fuzzy logic is a type of artificial intelligence, its history and applications are more recent than those of expert systems built on artificial intelligence. Problems with ambiguity, approximation, uncertainties, qualitative chaos, or partial truth are dealt with using fuzzy logic. As it can take assumptions into account, the fuzzy-based prediction model is progressively being used in the majority of fields related to resources and hydrology [19]. It can also be used effectively in situations involving missing data in long-term time series, data availability issues, time series prediction issues, etc. Operation of the proposed system has explained in Fig. 2.

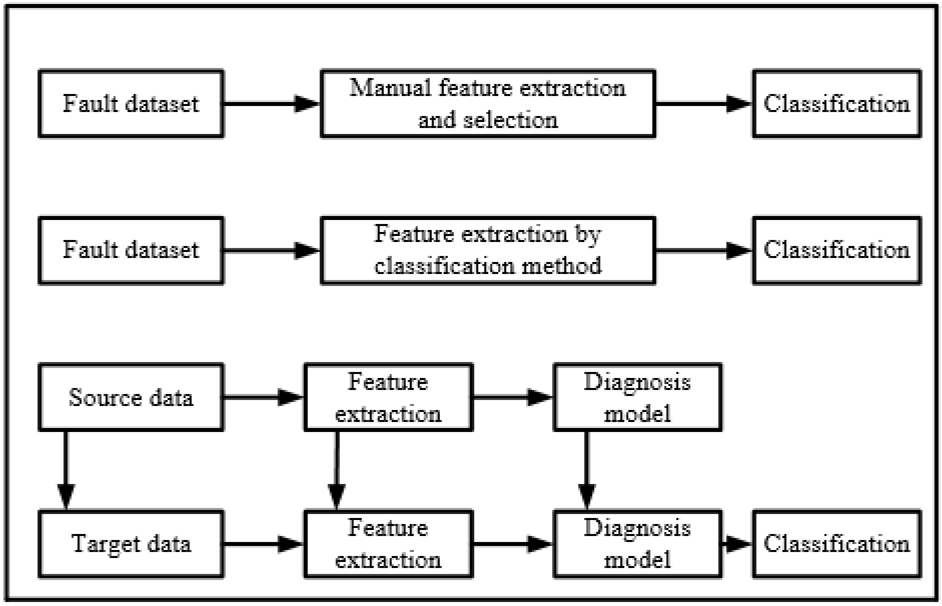

Fig. 2. Operation of the proposed system.

In the scenario of crisp input/crisp output systems, fuzzy logic contributes to parameter estimation. The implication is that, in many situations, using fuzzy logic is merely another type of exclamation. The use of fuzzy logic is frequently justified when the results of computing lines are too exact for an absolute mathematical realisation in fields with excellent mathematical imagery and solutions. Careful inspection of the comparison cases used to "prove" the benefits of fuzzy logic frequently reveals that they contrast the fuzzy approach with a relatively simple, non-optimized conventional approach. Due to the lack of formal explanations, it might be difficult or impossible in many situations to prove the individuality of fuzzy systems, especially when it comes to the stability of control systems, which is a crucial component [20].

In order to test the Supplemental information performance's accuracy, I's training datasets were combined, and the data was trained against the noise-free training dataset. The performance was then evaluated using the expanded database I's testing datasets for each noise level. The auto encoder effectively eliminated the interference from the data. Under different operational circumstances, sensors are used to collect the raw fault data, which includes a small quantity of target data and a large amount of data sources. The amount of sensors is equivalent to the amount of transmission media or dimensions. In order to prevent the problem of excessive deviation, raw data must typically be normalised through normalisation such that the quantity of each component falls within a given range.

A. Convolution Neural Network

CNN have attained cutting-edge performance in the challenges of feature extraction and image interpretation. Convolution and pooling are alternated in subsequent computational layers that contain CNNs (subsampling). Due to their very weak interconnection in each convolutional layer, CNNs are particularly simple to train with back propagation in comparison to other kinds of deep neural networks. Linear filters are employed for convolution in a convolutional layer. The parameters of the filtration serve as the primary CNN characteristics. An approach called variable exchange is used to lower the number of variables. Although described primarily lowers the systems' capacity, it increases their capacity for generalisation.

CNN classifiers are used to identify the fault in the manufacturing products. Its multi-layered design efficiently evaluates visual components and removes those that are superfluous. The CNN classifier consists of four layers: input, convolutional layer, pooling layer, fully connected layer, and output. Data pixel intensities in the dataset's range before a convolution neural network training. Throughout training, CNN is the system that operates the quickest. The information that is supplied for processing should all have the same size.

$$p(a,b) = \frac{O(a,b)-\mu}{\sigma} \tag{1}$$

1) Convolution layer: The convolution layer accepts some input data and computes the convolution of each input data using each filter. The filters have a direct impact on the features that are sought after in the given data.

$$f_i^m = x(\textstyle\sum_{j\in N_i} f_j^{m-1} * p_{ji}^m + a_i^m) \tag{2}$$

An input choice is represented by N_i- it. Additive bias is applied to the output map. b. The kernels used to map I are distinct for outcome maps j and k if the outcome mappings j and map k both sum over map i.

2) Max pooling layer: For the down - sampling layer, this layer is utilised to reduce fitting and reduce the size of the neurons. The Pooling layer cuts down on the number of parameters, computation rate, size of the feature map, training time, and overfitting. 100% of the training dataset and 50% of the test data are the criteria for classifier.

$$x_{mab} = max_{(s,t)\in} f_{mst} \tag{3}$$

The component at (s, t) in the pooling area mab known as Map, f_{mst} denotes a local neighbourhood surrounding the location (a, b).

3) Fully connected layer: In the context of fault detection, fully connected layers all of the convolution layers are put before the fully connected layer layers. The connection between the input and the output is mapped using the completely connected layer. The final levels of the network are fully connected layers. The result of the max pooling layer is the input of the fully connected layer.

4) Softmax layer: The scores are transformed into a balanced random distribution using the Softmax layer. The output is provided to the classifier as an input. Softmax is a well-known input classifier, and this layer applies the organisation of fault detection.

$$\sigma(\vec{X})_n = \frac{e^{x_n}}{\sum_{i=1}^{m} e^{x_i}} \tag{4}$$

B. F-CNN Method

Big data has become popular and widespread recently because of the information industry's quick expansion. Big data presents difficulties for deep learning models because of its bulk, variety, and rapid speed. The depth calculation methodology, meanwhile, has been shown to be successful for tensor space representation learning and hierarchy analysis of huge datasets. As a result, tensor must be used to describe the intricate huge data of fault detection dataset. Here, the entire space is divided into 32*32 small area blocks using a grid, and each small block uses the data for inflow and outflow. The placement of each small area block is represented by (i,j). Therefore, the tensor $xR2{*}i{*}j$. It can be used to represent the fault detection data for manufacturing industries area at any given time. As was already said, the internal analysis of the input, the uncertain informational defect, and the external environmental knowledge make up the entire input data for the Classification algorithm. Process of F-CNN method is explained in Fig. 3.

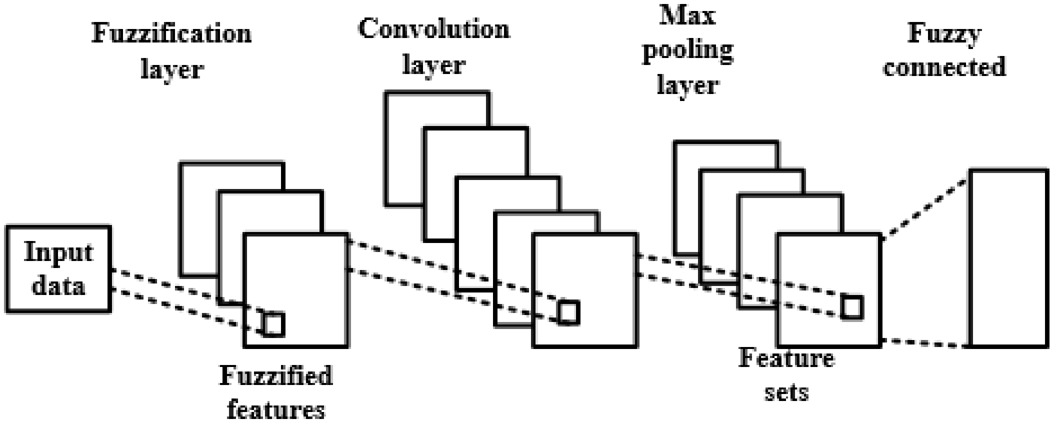

Fig. 3. Process of F-CNN method.

V. Result and Discussion

A. RMSE, MSE, AND MAE Analysis and Comparison

Three well-known assessment methods for fault prediction are mean square error, mean absolute error, and root mean square error. The appropriate computation process is as follows. These three criteria are used here to assess the suggested prediction approach. Comparison between MSE and RMSE and Comparison between MAE and RMSLE has given in Table I and II and the resultant graph has given in Fig. 4 and Fig. 5 respectively.

The extracted features are utilised to construct a training system. The model's training involves a lot of variables. The root mean squared error (RMSE) is used as the evaluating statistic while adjusting the hyper - parameters. Eq. (1) yields RMSE, which is the square root of variation, where x_p is the real value and x_q is the anticipated value. M denotes the sample group in terms of numbers. The standard error of the fit of the econometric system is another name for this statistics metric. A well-trained version has a low value of the RMSE, input signal is chosen in accordance with each tree, and a symmetric tree is utilised as the grow strategy. The cosine is the score product, and the RMSE is the loss function for training.

$$RMSE = \sqrt{\frac{1}{M}\sum\left(x_p - x_q\right)^2} \tag{5}$$

The distinction between the original cost and the predicted values is known as the mean squared error (MSE). Eq. (6) is used to extract it by squaring the dataset's mean squared error.

$$MSE = \frac{1}{m}\sum_{j=1}^{m}\left(X_j - Y_j\right) \tag{6}$$

The mean absolute error (MAE), which is regarded as the extreme variance mean for the dataset, illustrates the difference between the actual and projected values.

$$MAE = \frac{1}{P}\sum(W_a - W_b) \tag{7}$$

Eq. (8) yields the root mean squared logarithmic error (RMSLE). The connection in exponential terms between the real data value and the predicted values the model has predicted is known as the actual cause mean squared logarithmic deviation.

$$RMSLE = \sqrt{\frac{1}{N}\sum(\log(X_n\ + 1) - \log(X_m\ + 1))^2} \tag{8}$$

B. Improvement Analysis of RMSE AND MAE

The performance improvement amply demonstrates the worth and importance of the suggested approach. The Eq. (9) performs the enhancement of the evaluation.

$$E(m) = \frac{R_{op}^E - R_m^E}{R_{op}^E} \tag{9}$$

TABLE I. COMPARISON BETWEEN RMSE AND MSE

Name of the method	RMSE	MSE
ST-ResNet[21]	26.768	843.67
DeepST	35.896	725.02
ANN	28.543	627.01
SVR	17.654	351.21
F-CNN	16.564	221.03

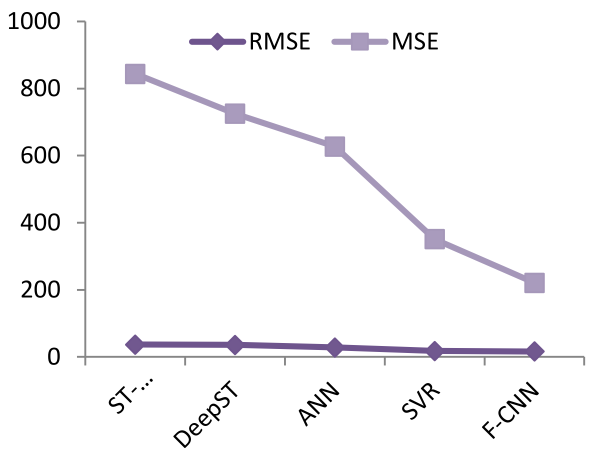

Fig. 4. Comparison between MSE and RMSE.

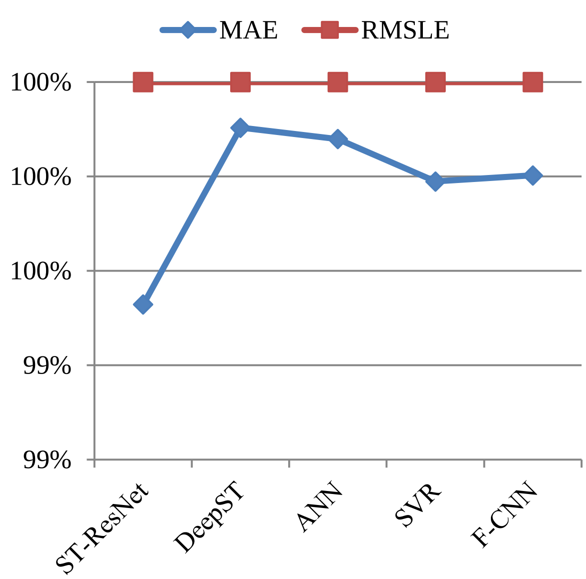

Fig. 5. Comparison between MAE and RMSLE.

Deep learning techniques include the ST-ResNet, DeepST, and F-CNN approaches that have been proposed. The model training procedure involves optimization modifications in order to produce predictions with greater accuracy. In the experiment, it was noted how the anticipated performance of the three models mentioned above changed over time. Each learning epoch involves only one learning procedure for all training samples, and at the end of each epoch, all parameters are changed once. F-CNN trained using an early stop approach for 26 epochs. The RMSE the number of epochs is displayed in Fig. 6. As can be seen from Fig. 6, the number of training epochs rises, which symbolises the convergence of the deep learning model. The F-CCN model can also learn the data more effectively than the other four models because it converges quicker and creates less RMSE. The comparison of various methods with proposed method has given in Table III and the result of the graph has given in Fig. 6.

Table II compares the performance of different techniques for a specific task, using Root Mean Square Error (RMSE) and the number of training epochs as metrics. ST-ResNet and DeepST are both specialized deep learning models for spatiotemporal data, with RMSE values of 67 and 56, respectively, indicating their prediction errors. ANN (Artificial Neural Network) and SVR (Support Vector Regression) show improved performance, with RMSE values of 45 and 38. The Fully Convolutional Neural Network (FCNN) outperforms all other methods with the lowest RMSE of 23, suggesting it provides the most accurate predictions. In terms of training time, measured in epochs, ST-ResNet and DeepST require fewer epochs (5 and 6.3), while ANN and SVR need more (14.3 and 21.5). FCNN, despite achieving the best accuracy, requires the most epochs (26), indicating a trade-off between training time and accuracy.

TABLE II. COMPARISON BETWEEN VARIOUS METHODS

Technique	ST-ResNet	DeepST	ANN	SVR	FCNN
RMSE	67	56	45	38	23
Epochs	5	6.3	14.3	21.5	26

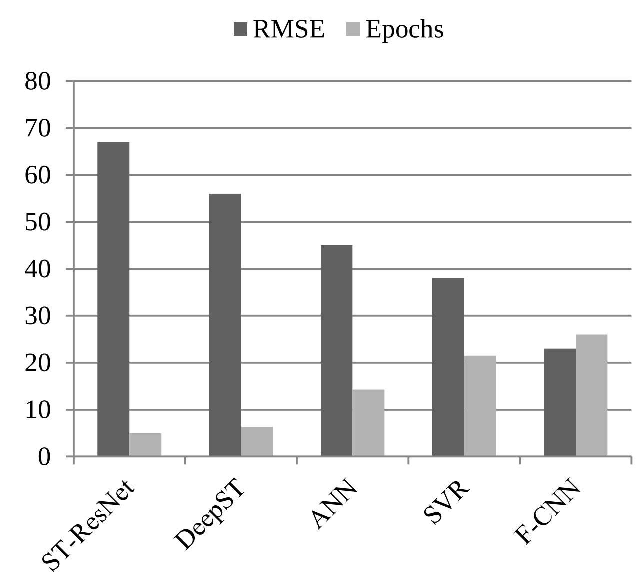

Fig. 6. The RMSE outcomes of three approaches throughout several epoch.

VI. Conclusion and Future Work

In real-world commercial processes, traditional defect diagnosis methods frequently fail because there aren't enough appropriate target domains with corresponding distributions. This study establishes a defect diagnostic framework based on F-CNN and uses broad information from large data sources to expedite the creation of a diagnosis engine for more manageable, similar datasets. In this study, manufacturing business data samples are used for experiments, and the convolutional framework of neural networks and measurement procedures used by credible manufacturers are examined. Employing convolutional neural networks, the research effectively addresses the nonlinear connection between input and output in performance review systems. The theory and implementation of convolutional neural networks in performance evaluation systems, as well as the performance assessment system index, are thoroughly examined. A model for assessing convolutional neural networks' performance is carefully created and repeated; encouraging testing outcomes highlight the model's effectiveness in performance evaluation. Based on defect prediction and performance enhancement, the experimental results show that the F-CNN technology is superior to other techniques. In industrial engineering, more research on deep learning for defect prediction is still necessary, even with the encouraging outcomes. In order to continually improve performance enhancement tactics, future research should concentrate on improving deep architectures in collaboration with industrial engineering disciplines. This study not only demonstrates the potential of F-CNN but also emphasises the continuous need for research and development in order to fully utilise deep learning for industrial applications.

References

[1] G. Mohmed, A. Lotfi, and A. Pourabdollah, “Enhanced fuzzy finite state machine for human activity modelling and recognition,” J. Ambient Intell. Humaniz. Comput., vol. 11, no. 12, pp. 6077–6091, Dec. 2020, doi: 10.1007/s12652-020-01917-z.

[2] J. Jiao, M. Zhao, J. Lin, and K. Liang, “A comprehensive review on convolutional neural network in machine fault diagnosis,” Neurocomputing, vol. 417, pp. 36–63, Dec. 2020, doi: 10.1016/j.neucom.2020.07.088.

[3] M. G. de Castro Ribeiro et al., “Detection and Classification of Faults in Aeronautical Gas Turbine Engine: a Comparison Between two Fuzzy Logic Systems,” in 2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Rio de Janeiro: IEEE, Jul. 2018, pp. 1–7. doi: 10.1109/FUZZ-IEEE.2018.8491444.

[4] S. Spalek, “Improving Industrial Engineering Performance through a Successful Project Management Office,” Eng. Econ., vol. 24, no. 2, pp. 88–98, Apr. 2013, doi: 10.5755/j01.ee.24.2.3087.

[5] M. Wu, W. Su, L. Chen, W. Pedrycz, and K. Hirota, “Two-Stage Fuzzy Fusion Based-Convolution Neural Network for Dynamic Emotion Recognition,” IEEE Trans. Affect. Comput., vol. 13, no. 2, pp. 805–817, Apr. 2022, doi: 10.1109/TAFFC.2020.2966440.

[6] W. Lv, J. Xiong, J. Shi, Y. Huang, and S. Qin, “A deep convolution generative adversarial networks based fuzzing framework for industry control protocols,” J. Intell. Manuf., vol. 32, no. 2, pp. 441–457, Feb. 2021, doi: 10.1007/s10845-020-01584-z.

[7] S. Spalek, “Improving Industrial Engineering Performance through a Successful Project Management Office,” Eng. Econ., vol. 24, no. 2, pp. 88–98, Apr. 2013, doi: 10.5755/j01.ee.24.2.3087.

[8] Z. Chengwei, “Research on Performance Evaluation System of Manufacturing Listed Companies Based on CNN,” in Proceedings of the 5th International Conference on Social Sciences and Economic Development (ICSSED 2020), Xi’an, China: Atlantis Press, 2020. doi: 10.2991/assehr.k.200331.049.

[9] H. Luo, C. Xiong, W. Fang, P. E. D. Love, B. Zhang, and X. Ouyang, “Convolutional neural networks: Computer vision-based workforce activity assessment in construction,” Autom. Constr., vol. 94, pp. 282–289, Oct. 2018, doi: 10.1016/j.autcon.2018.06.007.

[10] S. M. El-Shal and A. S. Morris, “A fuzzy expert system for fault detection in statistical process control of industrial processes,” IEEE Trans. Syst. Man Cybern. Part C Appl. Rev., vol. 30, no. 2, pp. 281–289, May 2000, doi: 10.1109/5326.868449.

[11] G. Tortorella, R. Miorando, R. Caiado, D. Nascimento, and A. Portioli Staudacher, “The mediating effect of employees’ involvement on the relationship between Industry 4.0 and operational performance improvement,” Total Qual. Manag. Bus. Excell., vol. 32, no. 1–2, pp. 119–133, Jan. 2021, doi: 10.1080/14783363.2018.1532789.

[12] A. Lütje and V. Wohlgemuth, “Tracking Sustainability Targets with Quantitative Indicator Systems for Performance Measurement of Industrial Symbiosis in Industrial Parks,” Adm. Sci., vol. 10, no. 1, p. 3, Jan. 2020, doi: 10.3390/admsci10010003.

[13] A. Dogan and D. Birant, “Machine learning and data mining in manufacturing,” Expert Syst. Appl., vol. 166, p. 114060, Mar. 2021, doi: 10.1016/j.eswa.2020.114060.

[14] R. Dubey, A. Gunasekaran, S. J. Childe, C. Blome, and T. Papadopoulos, “Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture,” Br. J. Manag., vol. 30, no. 2, pp. 341–361, Apr. 2019, doi: 10.1111/1467-8551.12355.

[15] A. A. Zadpoor, “Mechanical performance of additively manufactured meta-biomaterials,” Acta Biomater., vol. 85, pp. 41–59, Feb. 2019, doi: 10.1016/j.actbio.2018.12.038.

[16] P. H. M. Piratelo et al., “Blending Colored and Depth CNN Pipelines in an Ensemble Learning Classification Approach for Warehouse Application Using Synthetic and Real Data,” Machines, vol. 10, no. 1, p. 28, Dec. 2021, doi: 10.3390/machines10010028.

[17] B. Xiao, Q. Lin, and Y. Chen, “A vision-based method for automatic tracking of construction machines at nighttime based on deep learning illumination enhancement,” Autom. Constr., vol. 127, p. 103721, Jul. 2021, doi: 10.1016/j.autcon.2021.103721.

[18] B. Staar, M. Lütjen, and M. Freitag, “Anomaly detection with convolutional neural networks for industrial surface inspection,” Procedia CIRP, vol. 79, pp. 484–489, 2019, doi: 10.1016/j.procir.2019.02.123.

[19] N. Munir, J. Park, H.-J. Kim, S.-J. Song, and S.-S. Kang, “Performance enhancement of convolutional neural network for ultrasonic flaw classification by adopting autoencoder,” NDT E Int., vol. 111, p. 102218, Apr. 2020, doi: 10.1016/j.ndteint.2020.102218.

[20] S. Kambalimath and P. C. Deka, “A basic review of fuzzy logic applications in hydrology and water resources,” Appl. Water Sci., vol. 10, no. 8, p. 191, Aug. 2020, doi: 10.1007/s13201-020-01276-2.

[21] C. Wang, Y. Liang, and G. Tan, “Periodic residual learning for crowd flow forecasting,” in Proceedings of the 30th International Conference on Advances in Geographic Information Systems, Seattle Washington: ACM, Nov. 2022, pp. 1–10. doi: 10.1145/3557915.3560947.