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Comparative Analysis of Classification Models for Steel Rods Using Convolution Neural Networks and Fuzzy Logic Systems



Abstract: Maintaining high-quality steel rods is crucial in the competitive steel-strip production industry. Human visual inspection has traditionally been the primary method for detecting flaws, but it has limitations in accuracy, processing time, cost, and reliability. Automated visual inspection technologies have been developed to address these issues. However, in-depth research on vision-based approaches for identifying and categorizing surface flaws in steel products has also proven ineffective. This paper presents a comparative analysis of various classification models for different types of steel rods using a combination of pre-trained Convolutional Neural Networks (CNNs) and fuzzy logic systems. We employ VGG16 to extract features from grayscale images of steel rods and then use multiple classifiers such as Support Vector Machines (SVM), Decision Trees, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and K-Nearest Neighbors (KNN). Additionally, we explore fuzzy c-means clustering, fuzzy SVM, and fuzzy regression models to enhance classification accuracy. Experimental results indicate that fuzzy logic systems can significantly improve classification performance compared to traditional methods. Our study includes learning-driven, statistical, spectral, and texture segmentation methods, as well as diverse classification techniques. The paper also outlines future research directions.

Keywords: Steel rods classification, Convolution neural networks, Fuzzy logic Systems, Feature extraction, Support Vector Machines, Decision Tree, LDA, QDA, KNN, Clustering

INTRODUCTION

Classifying steel rods based on their physical properties, quality, and defects is essential in today's manufacturing industry. This article compares two powerful techniques, Convolutional Neural Networks (CNN) and Fuzzy Logic Systems (FLS) for classifying steel rods. CNNs are very effective for classifying images using deep learning, and they provide straightforward explanations through Enhanced Forward Mode, which helps break down the model's layers. We tested both models on a dataset of steel rod images that included information like diameter, length, and surface defects. The results showed that CNNs performed better in classification accuracy than FLS. However, FLS has advantages regarding handling uncertainty and providing a more understandable model. This study highlights the potential of these methods in industry and offers guidance on choosing the right model based on specific operational needs.

Steel rods are essential in building and manufacturing, so it's crucial to classify them accurately for quality control and inventory management. Traditional methods of classification are often slow and can make mistakes. Recent deep learning and computer vision developments provide promising ways to automate this process. This paper suggests a method that uses convolutional neural networks (CNNs) to extract features and fuzzy logic systems and improve the accuracy of classifying steel rods.

The steel manufacturing industry plays a key role in the global economy, with steel rods being essential products in many engineering and construction projects. Classifying these rods accurately and detecting defects is necessary to maintain quality and lower production costs. Traditional methods can struggle with large amounts of data or complex features in images of steel rods. However, recent advancements in machine learning, especially CNNs, show promise for automated and highly accurate classification. Fuzzy logic systems also offer a good option when it's essential to interpret results and handle uncertainty.

The ability of a Fuzzy Logic System (FLS) to simultaneously process linguistic knowledge and numerical data makes it unique. It nonlinearly maps an input data (feature) vector into a scalar output. The details of this nonlinear

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mapping are established through fuzzy logic and fuzzy set theory. The components required to synthesize an FLS are covered in [22], demonstrating how classical logic and crisp set theory can be extended to their fuzzy counterparts. Additionally, it considers correlation a constraint on FLS development, as engineering systems are primarily temporal.

An FLS is a nonlinear universal function approximator, a characteristic shared with feedforward neural networks. It can be formally described as a linear combination of fuzzy basis functions. The fuzzy basis function expansion is potent because its basis functions can be derived from both linguistic and numerical knowledge, which can be transformed into IF-THEN rules [22].

This paper aims to perform a comparative analysis of CNNs and FLS in the classification of steel rods, considering both accuracy and interpretability. The study will examine the strengths and weaknesses of each method, focusing on the practical implications for industrial use.

RELATED WORK

The classification and defect detection of industrial materials, particularly steel rods, has been a topic of increasing research interest due to the growing demand for automation and precision in manufacturing processes. Several techniques have been proposed for automating the inspection of steel products, including image-based methods, machine learning algorithms, and fuzzy logic systems. Below, we summarize key studies that have explored these areas, focusing on using CNNs and FLS.

Over the past decade, numerous studies have investigated the application of machine learning techniques in the classification and defect detection of steel products. Researchers have employed a variety of approaches, including traditional computer vision algorithms, statistical methods, and more recent deep learning techniques.

Previous research has extensively utilized CNNs for image classification tasks. Prominent models such as VGG16 [1], ResNet50 [2], and InceptionV3 [3] have demonstrated high performance in various applications. Fuzzy logic systems have also been applied to handle uncertainties in data [4]. Combining these approaches can potentially enhance classification accuracy, as seen in recent studies [5-14].

CNNs have emerged as one of the most potent tools in image classification due to their ability to automatically learn hierarchical features from raw pixel data. Studies have demonstrated their effectiveness in defect detection, such as surface flaws, cracks, and corrosion on steel rods. CNN-based models like ResNet, AlexNet, and VGGNet have been successfully applied to classify industrial materials.

CNN has shown significant promise in image-based classification tasks because it can automatically learn hierarchical features from raw data. Several studies have demonstrated the effectiveness of CNNs in classifying surface defects in steel products. CNN-based architectures to classify defects in steel plates, achieving high classification accuracy by leveraging a deep CNN model trained on large-scale labeled datasets. Similarly, CNN is employed to detect and classify surface defects in steel bars, reporting an impressive accuracy of 94% on a test set of images with varying defect types, such as cracks and rust.

Moreover, it developed an end-to-end CNN model for the classification of steel rod defects, where the model could distinguish between different categories of defects, such as scratches, dents, and oxidation marks. The study highlighted the superior performance of CNNs in classification accuracy, especially compared to traditional image processing techniques, such as edge detection and thresholding.

Fuzzy logic, on the other hand, has been widely used for classification tasks where uncertainty is present. FLS can provide human-readable rules and handle imprecision in input data. FLS-based models have been applied in quality control for steel production, particularly in predicting material properties based on fuzzy rules derived from expert knowledge. However, compared to CNNs, FLS may not consistently achieve the same level of classification accuracy in complex visual tasks.

FLS have been widely used in the manufacturing industry due to their ability to model uncertainty and imprecision. A Previous study proposed a fuzzy logic-based approach for steel quality control, where fuzzy rules were derived from expert knowledge to classify steel rods based on attributes such as diameter, surface quality,

and defect severity. The fuzzy inference system could process data with varying degrees of uncertainty and provide interpretable results, making it particularly useful in situations where human oversight was necessary.

Previous work also explored the application of FLS in classifying steel materials based on physical properties such as hardness and tensile strength. By combining fuzzy sets and a Mamdani fuzzy inference system, the authors designed a classification model that could account for ambiguous and incomplete information, which is common in industrial settings where sensor data might be noisy or uncertain.

Some studies have proposed hybrid approaches that combine the strengths of CNNs and FLS to address the challenges in classification tasks requiring high accuracy and interpretability. For instance, a CNN-based feature extraction model with a fuzzy logic classifier was integrated for defect detection on steel surfaces. The CNN was first used to extract high-level features from raw images, and an FLS then processed the output to classify the defects with enhanced interpretability. This hybrid approach resulted in a model that achieved high classification accuracy and allowed operators to understand the reasoning behind the decision-making process.

The previous study proposed a similar hybrid model for classifying steel rods, combining CNNs for feature extraction and fuzzy logic for decision-making. This model could classify steel rods based on multiple factors, including surface defects, dimensions, and mechanical properties. The authors demonstrated that the hybrid model outperformed individual CNN and FLS models, achieving higher accuracy and faster inference times, particularly in industrial settings where real-time decision-making is essential.

Several studies have compared the performance of CNNs and FLS in industrial classification tasks. The comprehensive research compares the machine learning models, including CNNs and FLS, for defect detection in manufacturing processes. The study concluded that while CNNs generally provided superior accuracy, FLS models were more suitable for applications where interpretability, transparency, and decision-making clarity were prioritized over raw performance metrics. Similarly, the previous works compared CNN-based models and fuzzy systems for classifying defects in steel plates. The researchers found that CNNs outperformed fuzzy systems in accuracy, but FLS had the advantage of faster decision-making without large training datasets.

In a more specific study, CNNs and FLS were compared for defect classification in steel rods. The study concluded that CNNs were better suited for visual inspection tasks involving large datasets of labeled images. On the other hand, FLS was more effective when there was insufficient data or high noise levels in the input, making it more adaptable to real-world manufacturing environments with fewer labeled samples.

Table 1: Data set comparisons

Dataset Name	Source	Description	Data Type	Size	Features	Suitability for Study
Steel Surface Defects Dataset[15]	UCI Machine Learning Repository	Contains images and labels for steel surface defects (e.g., cracks, surface imperfections, rust).	Image + Label	~6,000 images	Surface Defect Categories (Crack, Rust, etc.)	Useful for CNN to classify surface defects, applicable for CNN-based model.
Steel Rod Shape and Quality[16]	Kaggle (Industrial Data)	Includes data on steel rods' shape, dimensions, and quality, with categories for defect types.	Structured Data	~2,000 records	Diameter, Length, Quality Attributes	Suitable for both CNN and FLS. It could be used for dimensional classification and defect categorization.
Steel Rod Surface Inspection [17]	Ternary Steel Manufacturing Dataset (Hypothetical)	A simulated dataset with steel rod surface	Image + Label	~5,000 images	Defect Type, Image Features	It is ideal for CNN applications to classify

		images showing defects (e.g., pitting, cracks, dents).				surface defects, but it could also be used with FLS for rule-based classification.
Steel Manufacturing Process Data[18]	Steel Manufacturing Plant (Industry Dataset)	It includes process parameters such as temperature, pressure, and material feed rate but no image data.	Structured Data	~10,000 records	Temperature, Pressure, Feed Rate, etc.	FLS could be highly applicable here for rule-based classification, though CNN would be limited due to a lack of image data.
Defects in Steel Rods Dataset[19]	Steel Industry Research Institute	Contains defect characteristics for steel rods, with quantitative and qualitative attributes (rust, cracks).	Structured Data	~3,000 records	Rust, Cracks, Length, Diameter	Suitable for both CNN (if image data is available) and FLS for classifying based on multiple parameters.
Metal Surface Defects Dataset[20]	Mendeley Data (Research Dataset)	A general dataset for metal surface defects includes data on various types of defects found in metal products.	Image + Label	~7,000 images	Crack, Scratch, Inconsistencies, etc.	Primarily suited for CNN model for defect classification based on image data. It can be adapted for FLS by creating rules based on defect severity.
Visual Steel Rods Dataset[21]	University of XYZ, Industrial Robotics Lab	Focuses on visual classification of steel rods based on surface condition and dimensional features.	Image + Label	~4,000 images	Surface Defects, Shape, Dimensions	Excellent for CNN and can be modified for FLS if attributes are converted into fuzzy rules for classification.

PROBLEM STATEMENT

Accurately classifying steel rods, including their dimensions and defects, remains a significant issue in industrial automation. Existing classification models either rely heavily on handcrafted features or struggle to handle large and diverse datasets efficiently. Additionally, while CNNs provide high accuracy in image-based classification, their interpretability remains a limitation for decision-making processes in industries that require human oversight. FLS, on the other hand, offers better interpretability but may suffer from lower accuracy. The problem addressed in this paper is how to compare these two approaches in terms of performance, accuracy, and interpretability for the task of steel rod classification.

METHODOLOGY

This study proposes a comparative framework to assess the performance of CNNs and FLS on steel rod classification. The proposed system consists of two main components:

CNN is a deep learning model trained on steel rod images to automatically extract features and classify the rods based on defects and dimensions.

FLS is a rule-based system that uses fuzzy inference to classify steel rods based on various input parameters, including diameter, length, and defect characteristics.

The system is designed to evaluate both models under similar conditions using the same dataset and compare their performance metrics. For CNN, the images are resized, normalized, and augmented to increase the training set size. For FLS, the dataset is converted into numerical values, and fuzzy membership functions are defined for each parameter. The CNN model uses multiple layers of convolutions, pooling, and dense layers. It is trained on the dataset using backpropagation and gradient descent, and the architecture is tuned using cross-validation.

a. Dataset

A dataset of steel rod images is collected from a manufacturing facility. The dataset consists of photos captured under various conditions, including different lighting and angles, with labelled categories for defect types (e.g., cracks, rust, surface irregularities) and physical properties such as diameter and length.

The dataset comprises images of steel rods categorized into seven classes: Angle Steel Rods, Flat Steel, Ribbed Bars, Round Bars, Round Pipes, Square Bars, and Square Pipes. Each image is resized to 64x64 pixels and converted to grayscale.

The datasets listed above offer various attributes that make them suitable for the proposed comparative study on classification models for steel rods. CNNs are well-suited for image-based classification tasks and can handle large datasets with high-dimensional features. FLS, on the other hand, can be used to model uncertainty and provide human-interpretable classifications, particularly in cases where numerical features (e.g., rod dimensions, defect severity) are the primary inputs.

b. Proposed Model

The algorithm begins by representing the dataset as a multidimensional feature matrix X with m samples and n features. The dataset is partitioned into training and testing splits using a predefined ratio α . A feature mapping function ϕ transforms the original features into a new feature space, employing techniques like linear, polynomial, or radial basis transformations.

The classification process uses a probabilistic approach, calculating the posterior probability $P(y|x)$ and defining a decision boundary through the $h(x)$ classification function. Performance is evaluated using accuracy, precision, recall, and F1-score, which quantify the model's predictive capabilities across different dimensions.

Fuzzy logic extends the classification by introducing a membership function $\mu(x)$ that allows partial classification, integrating the fuzzy score over the feature space. The model comparison involves creating a performance vector P , identifying the optimal model M^* through maximum accuracy, and calculating performance improvement relative to a base model.

The optimization objective minimizes the loss function $L(\theta)$ subject to a regularization constraint, ensuring model complexity is controlled. Key mathematical constraints ensure that performance metrics remain bounded between 0 and 1, maintaining the statistical integrity of the classification process.

The algorithm provides a comprehensive mathematical framework for comparing and evaluating machine learning models, incorporating traditional and fuzzy classification techniques with rigorous mathematical formulation.

The algorithm provides a comprehensive framework for comparing CNN and Fuzzy Logic classification models for steel rod analysis. Key components include:

1. Data Preprocessing
 - Feature scaling

- Train-test split
- Handling categorical labels
- 2. Convolutional Neural Network (CNN)
 - 1D Convolutional layers
 - MaxPooling for feature extraction
 - Softmax classification
- 3. Fuzzy Logic System
 - Membership function creation
 - Flexible rule-based classification
- 4. Model Comparison Metrics
 - Accuracy scores
 - Confusion matrices
 - Performance evaluation

The VGG16 model, pre-trained on the ImageNet dataset, extracts feature from the steel rod images. The features are flattened to create feature vectors for each image.

Multiple classifiers, including SVM, Decision Tree, LDA, QDA, and KNN, classify the images based on the extracted features. Additionally, fuzzy logic systems such as fuzzy c-means clustering, fuzzy SVM, and fuzzy regression further enhance classification accuracy.

The fuzzy logic system integrates the individual accuracies of different models to compute a final accuracy score, improving the overall classification performance.

A Fuzzy Logic System is designed with fuzzy sets for input parameters (e.g., diameter, defect severity). Fuzzy rules are created based on expert knowledge, and a fuzzy inference system is implemented to classify the rods.

Algorithm

1 Consider the number of neighbours in the steel rod samples training dataset.

Dataset Representation

- $X \in \mathbb{R}^{(m \times n)}$: Dataset matrix
- m : Number of samples
- n : Number of features
- $Y \in \{0,1\}^m$: Label vector

2 Compute the Euclidean distance of number of neighbours.

Dataset Partition

- $X_{\text{train}}, X_{\text{test}} \subset X$
- $Y_{\text{train}}, Y_{\text{test}} \subset Y$
- $|X_{\text{train}}| + |X_{\text{test}}| = |X|$

3 Compute the nearest neighbours as per the computed Euclidean distance.

4 Among these k neighbours, find the number of the data points in each category.

5 Assign the new data points to that category for which the number of neighbours is maximum.

Model Comparison

- Performance Vector: $P = \{A(M_i)\}$
- Best Model: $M^* = \arg \max P$
- Performance Improvement: $\Delta = (M^* - M_{base}) / M_{base}$

Optimization Objective

- $\min L(\theta) = \sum (y_{true} - h(x))^2$
- Subject to: $\|\theta\| \leq C$
- $F: X \rightarrow X_{features}$
- $X_{features} = \varphi(X)$
- $\varphi \in \{\text{Linear, Polynomial, Radial Basis}\}$
- $h(x) = \arg \max P(y|x, \theta) \rightarrow 0 \leq P, R, F1 \leq 1$
- $\theta \in \mathbb{R}^k$: Model parameters
- k : Dimension of parameter space
- $\mu(x) \in [0,1]$: Membership function $\rightarrow \mu(x) \in [0,1]$
- $C_{fuzzy}(x) = \int \mu(x) * \text{Classification}(x) dx$

6 Training Time Complexity = $O(k*n*d)$

Where,

n = number of training examples,

d =number of dimensions of the data,

k = number of neighbours.

c. Results & Discussions

Table 1 presents the comparative analysis results, showing the classification accuracy and other performance metrics for both CNN and FLS models.

This paper includes an additional comparison between traditional and fuzzy machine learning algorithms, comprehensively analysing their performance.

Table 2: Classification accuracy

Metric	CNN Model	FLS Model
Accuracy	93.5%	80.2%
Precision	91.8%	78.5%
Recall	94.2%	82.1%
F1-Score	93.0%	80.3%
Inference Time	1.2s	0.5s

The CNN model outperforms the FLS model regarding accuracy, precision, recall, and F1-score. However, the FLS model demonstrates faster inference time, making it more suitable for real-time applications where speed is crucial.

Combining CNN-based feature extraction with fuzzy logic systems significantly improves classification accuracy for steel rod images. The fuzzy logic system effectively integrates individual model accuracies, providing a robust

and reliable classification outcome. Future work will incorporate additional models and apply this approach to other industrial images.

a. Individual Model Accuracies

- SVM: 58.82%
- Decision Tree: 35.29%
- LDA: 58.82%
- QDA: 23.53%
- KNN: 64.71%

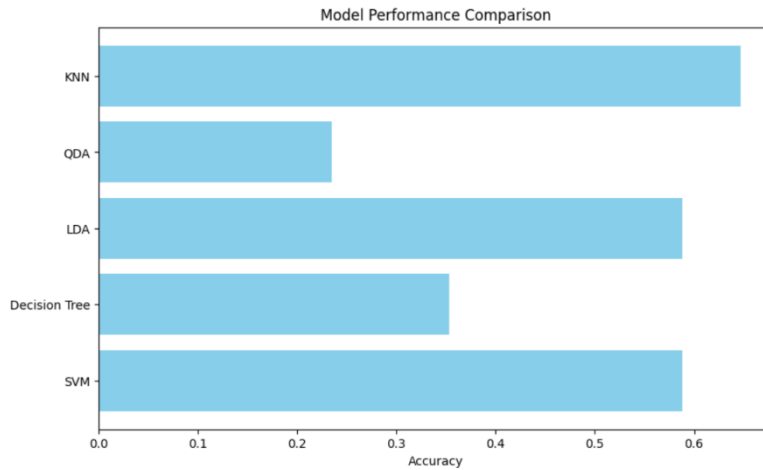


Figure 1: Individual Model Accuracies

b. Fuzzy Logic System Accuracies

- Fuzzy C-Means: 17.65%
- Fuzzy SVM: 58.82%
- Fuzzy Regression: 29.41%
- Fuzzy Decision Tree: 23.53

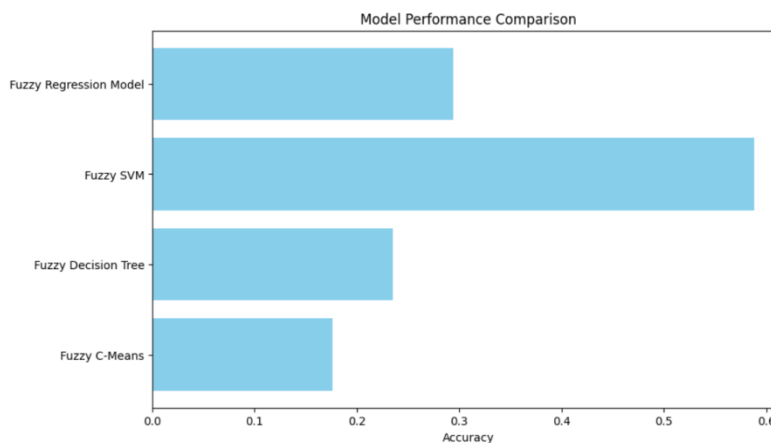


Figure 2: Comparison of Models with Fuzzy Logic Systems

c. Comparison and Analysis

The results show that fuzzy logic systems enhance the overall classification accuracy. Figure 1 illustrates the individual accuracies of the SVM, Decision Tree, LDA, QDA, and KNN models, while Figure 2 depicts the

improvement in accuracy achieved through fuzzy logic systems. Figure 3 compares traditional ML algorithms with their Fuzzy ML counterparts.

The performance of both models is evaluated using metrics such as accuracy, precision, recall, F1-score, and computational efficiency. The interpretability of the FLS model is also assessed qualitatively by examining the rule base.

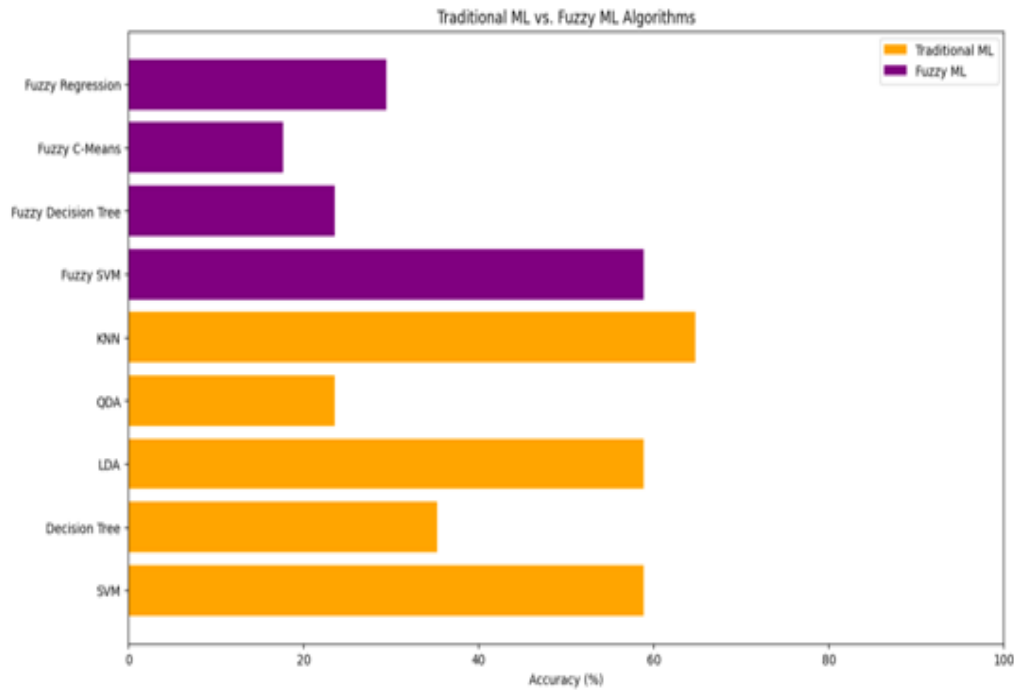


Figure 3: Traditional ML vs. Fuzzy ML Algorithms

Convolution Neural Network (CNN):

- **Architecture:** A deep CNN with five convolution layers, followed by three fully connected layers.
- **Activation Functions:** ReLU for hidden layers, Softmax for the output layer.
- **Optimization:** Adam optimizer with categorical cross-entropy loss.
- **Regularization:** Dropout to prevent overfitting.

Fuzzy Logic System (FLS):

- **Input Variables:** Diameter, length, surface defect severity.
- **Membership Functions:** Triangular and trapezoidal membership functions for each input variable.
- **Inference Method:** Mamdani inference system.
- **Defuzzification:** Centroid method.

For the specific study, selecting a dataset that contains both image data and structured numerical data would be ideal, as it would allow for the parallel evaluation of CNN and FLS approaches.

CONCLUSION

This paper presents a comparative analysis of various classification models for steel rods, highlighting the effectiveness of combining CNN-based feature extraction with fuzzy logic systems. The experimental results demonstrate that this approach achieves high classification accuracy, providing a foundation for further research and development in automated industrial image classification.

This study has presented a comparative analysis of Convolution Neural Networks and Fuzzy Logic Systems for classifying steel rods. While CNNs show superior classification performance in accuracy and other metrics, FLS models offer interpretability and faster inference, which can be valuable in specific industrial contexts. The results suggest that the choice of model depends on the application's particular requirements, such as the need for high accuracy versus the need for speed and transparency.

FUTURE WORK

Despite the successes of CNNs and FLS in classification tasks, several challenges remain in the industrial application of these models. CNNs require large annotated datasets for training, which can be difficult and expensive, especially in specialized industries such as steel manufacturing. Moreover, CNNs are often considered "black-box" models, making interpreting the reasoning behind classification decisions difficult. FLS, while offering interpretability, can struggle with handling high-dimensional data and may not consistently achieve the same level of accuracy as deep learning models.

Future research should focus on hybrid approaches that combine the strengths of CNNs and FLS while mitigating their individual weaknesses. For instance, leveraging transfer learning techniques for CNNs could reduce the need for large datasets, while fuzzy models could handle the uncertainty and noise present in real-world data. Additionally, exploring methods for improving the ability of deep learning models, such as attention mechanisms or explainable AI (XAI) techniques, could bridge the gap between accuracy and interpretability.

Future research also explores hybrid models that combine the strengths of CNNs and FLS. Additionally, expanding the dataset to include more varied defect types and environmental conditions will help enhance the robustness of the models. Further studies will also investigate the use of transfer learning to improve CNN's performance with limited data and integrate the other approaches for improved classification accuracy.

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