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SMART CNN-BASED DEFECT DETECTION OF STEEL PLATE MANUFACTURING PLANTS

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ABSTRACT

Steel plate manufacturing calls for precision and quality assurance in order to minimize surface defects compromising performance and market value. This paper presents a smart CNN-based approach for the real-time detection and classification of defects in the manufacture of steel plates. Using the Kaggle steel surface defect dataset and MATLAB 2022b simulations, this work proposes an efficient CNN model for identifying various classes of surface flaws, including crazing, folding, inclusions, rolled-in scale, and scratches. The results indicate that when trained with 5000 images, the overall classification accuracy of the proposed model achieves 98.23%, outperforming that of traditional feature-based methods significantly. The research validates the fact that CNN-based detection of defects can significantly promote industrial automation, reliability in inspection, and efficiency in production.

KEYWORDS: Defect detection, Convolution Neural Network, Steel plate, Industrial automation, Real-time inspection

1. INTRODUCTION

Steel is extremely important to modern manufacturing for a variety of industries, including construction, automotive, marine, and machinery. As each industry continues to push its materials towards higher performance requirements, there is also an increasing need for steel plates that are properly machined and finished. A small surface imperfection on a steel plate (i.e. scratch, dent, imperfection, pitting, or roller mark) will decrease the mechanical integrity of the plate; in turn, decreasing the expected useful-load capability of the plate; thereby affecting the quality of the finished components that are made from the steel plate before it leaves the production facility. (Mengesha, 2025).

Convolutional Neural Network (CNN) defect detection is a mechanized process utilizing Convolutional Neural Networks to automatically identify and categorize defect types based on image captures made during the inspection phase in manufacturing. CNNs utilize the power of deep learning to learn visual features automatically from unprocessed image data so that they can identify the fine-texture, shapes, and surface characteristics of different types of surface flaws. When comparing traditional defect detection methods that rely on pre-defined feature extraction methods, CNN-based methods can effectively extract relevant data in real-time with high levels of accuracy, making them an excellent option for automated inspection solutions within manufacturing. (Hou et al., 2024).

Steel manufacturing plants usually have defects that are either visible or not visible when they are produced. They can result from mechanical failures, faulty finishing processes, sudden changes in temperature, and/or impurity in the material used for production. Examples of defects are, crazing, folding, unused parts and scratches; however, each will negatively affect the performance, appearance and saleability of steel products. Timely discovery of defects is critical to preserving product quality, maximizing yield, and achieving dependability for the user of the product in an industrial setting. (Vasan et al., 2024)

These shortcomings have led to the development of automated inspection systems for use in manufacturing industries by utilizing legacy computer vision and/or machine learning systems. Conventional approaches, such as statistical feature extraction, texture analysis, edge detection, and Support Vector Machines, attempt to model defect characteristics using hand-engineered visual features, such as gray-level co-occurrence matrices, geometric descriptors, and frequency-domain patterns. These techniques have produced great results when tested at small scales in controlled environments; however, they will be compromised when faced with the complexity of a large range of defect types, variable lighting and noisy production conditions, among other issues. Because they rely on manually engineered features, they typically cannot show the same type of flexibility and scalability than what is required to deal with the large range of real-world conditions that may be encountered. (Santelices et al., 2025).

The most recent developments in deep learning, especially CNNs, have completely revolutionized industrial surface inspection. The CNNs can automatically learn hierarchical discriminative feature representations directly from the raw data of images without any human intervention in feature engineering. The generalization power across the variations in texture, scale, and illumination leads to very accurate adaptive detection of defects in situations of difficult operational settings. Besides, CNN-based models can be integrated into real-time production systems with fast inference speeds suitable for high-throughput manufacturing lines (Khanam et al., 2024).

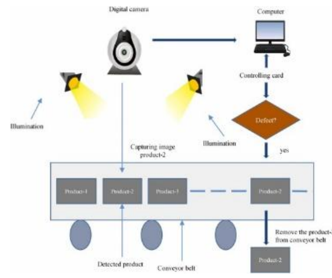

Figure 1: Deep CNN-based visual defect detection Source: (Jha & Babiceanu, 2023).

This research is centered on creating an intelligent Convolutional Neural Network to detect and classify surface defects on steel plate surfaces. The dataset used for training will come from Kaggle, which will have multiple defect categories including crazing, folding, inclusions, rolled-in scale, pitted surfaces, and scratch defects.

Additionally, the project will investigate how the quantity of training data impacts detection accuracy, how robust the trained model is under Gaussian noise conditions, how well the intelligent model compares to the established feature-based approach, and whether it is practical to use this new intelligent model in real-time industrial inspection processes to develop greater automation, minimize human error, and ultimately facilitate greater efficiency within the manufacturing process.

2. LITERATURE REVIEW

The increase in steel demand globally continues to grow because of many industries' reliance on the use of steel as a material for their operations, including construction, automotive, national defense, machinery, chemicals and manufacturing industries (Indrawati S., 2019). In the U.S. alone, 98 million metric tons of steel were consumed during 2021 (Indrawati S. 2019). To ensure that steel products have high-quality characteristics and are structurally sound and functional, it is critical to have low surface defects on them. Steel products that have defects do not conform to the lean principles of production since they cause waste and high cost, as well as reducing efficiency. Lean manufacturing strives to provide quality output with as little use of resources as possible; therefore, it focuses on the elimination of waste while increasing efficiency (Radecka K. 2022).

The process of making steel consists of several operations: heating, rolling, cooling and cutting. Each of these processes may subject a steel surface to contact with many different types of machinery; as a result, the steel surface may develop a defect before it is shipped out as an end product. Qian (2019) identified a number of different types of defects, including, but not limited to, cracks, scabs, edge curling, holes and wear. The existence of defects in a steel product will have direct impacts on the product's ability to resist corrosion, its structural integrity and the profitability of the manufacturer producing it. The increase in steel demand has created an opportunity for the steel industry to enhance their efficiency through optimizing their production processes. In accordance with Lean principles for efficient operations, these methods may result in production bottlenecks, thereby prolonging lead times and obstructing flow (Leksic I, 2020). Enhancing this method can be achieved by employing computer vision for defect classification. Industries including wood, glass, printed circuit boards, and steel have acknowledged the necessity of automated defect detection utilizing Convolutional Neural Networks (CNNs) (Akhyar F, 2019). Organizations can conserve time and costs, reduce human error, and enhance production efficiency by automating the fault identification process. The disparity in class distribution and the extensive background region relative to the defect area hinder feature extraction due to the unpredictability and diversity of metal surface flaws (Shahin M, 2023). New machine vision algorithms for metal surface identification are more efficient, versatile, and accurate than human examinations (Liu W., 2022).

Utilizing computer vision technology for automated inspection is one method to attain Lean manufacturing objectives. Selecting the appropriate convolutional neural network (CNN) model is essential as it influences the efficacy of the defect detection system and its alignment with Lean manufacturing goals (Hosseinzadeh et al., 2025)

Our primary emphasis is on 'defects,' as it directly impacts product integrity and expenses. Lean manufacturing is typically defined by the acronym "TIMWOOD," which represents Transportation, Inventory, Motion, Waiting, Overproduction, Overprocessing, and Defects. We concentrate on enhancing the precision of CNN-based inspections to minimize waste resulting from flaws, while also addressing methods to augment the speed and reliability of automated inspections to decrease waiting times and overprocessing.

3. METHODOLOGY

Convolutional Neural Network (CNN) Architecture

The proposed defect detection system is based on a seven-layer convolutional neural network, specifically designed to learn features and classify surface anomalies from steel plate images. The model initiates with an input layer that takes 40×40 grayscale images from the steel defect dataset. Grayscale representation was used to reduce the computational cost while still preserving necessary textural and contrast information, which characterizes different defect patterns. Following the input stage, the network includes two convolutional layers, with each using a 5×5 filter that systematically scans the image for the capture of localized spatial features. The convolutional layer at the base level will locate common themes, for instance: edges of a surface, vertexes of a surface, simple textures of a surface. The second convolutional layer will extract specific defect features that are more complicated than those of the other defect features extracted by the first layer, and include: contours of deformed surfaces, irregular patterns on surfaces and inconsistencies of very fine structure on surfaces. After performing the series of convolution operations, they were followed by a 'ReLU' function, that effectively introduces non-linearity into the model and assists speed in convergence, by limiting the impact of vanishing gradation problems. Lastly, max pooling was applied with a window of 2x2 to downsample the feature maps, eliminate as much spatial dimension data as possible, along with cutting costs associated with computational time, to increase resiliency of models with respect to small distortion and noise due to movement. The output of the pooling layer is flattened and passed to a fully connected layer, which integrates the extracted high-level features to interpret their relationship with distinct defect categories. The output layer employs Softmax to obtain normalized probability distributions across all defect classes, allowing the accurate multi-class classification of defects (Duarte et al., 2025).

4. WEIGHT INITIALIZATION AND LEARNING

The initial weights of the CNN are generated by training a three-layer sparse autoencoder on 24,000 randomly extracted 5×5 patches from the steel surface dataset. In such a way, the network could learn the most fundamental structural patterns that might further help in effectively training the model in a supervised manner. By initializing the model with pre-trained weights, which already capture relevant edge and texture features, there is less chance of finding a poor local minimum as well as an improved stability and effectiveness of the learning process for CNNs. Training was completed using an alternative approach of training using backpropagation, along with back-propagation through an estimated loss using the softmax loss function which identifies how well its predictions matched the actual defect classes. In addition, additional constraints were used during optimization in order to continue to limit overfitting by the network and therefore include only those features that were most beneficial to the model. Through this process of pre-training based on a sparse autoencoder and Regularized Supervised Learning, the speed with which convergence is achieved and the general performance of the model has improved. (Kurochkin et al., 2025).

5. DATASET AND EXPERIMENTAL SETUP

Kaggle's Steel Surface Defect Dataset was employed in this investigation and is an established standard reference dataset of steel surface defects and contains pictures depicting various defects found on steel surfaces. The dataset includes images for six classes of defects (crazing, folding, inclusion, rolled-in scale, pitted surface, and scratch), in addition to one class for images of non-defective (normal) steel. The groupings of defect classes provide a representative sample of the actual defect patterns typically found in the steel industry's manufacturing process. The dataset was split into separate training and testing datasets so that the experiments could be run to compare the accuracy of predictive capacity in both controlled and varying environments. The modelling and simulations were performed on a desktop computer using MATLAB 2022B, with the PC having an NVIDIA GTX 970 graphics card and 4 GB of RAM, which had sufficient processing power to support deep learning applications. In addition to providing a means to quantify the strength of models built using CNNs, evaluating model construction with respect to real-world applications involved augmenting test images by adding artificial Gaussian noise to the image data at three levels of SNR (35 dB, 25 dB, and 15 dB). This method simulates variations in acquiring images in real-world applications due to different lighting conditions, sensors' limitations, and external environmental factors and, therefore, provides an assessment of the ability of the CNNs to deliver accurate results in noisy and imperfectly obtained images. (Yousra et al., 2024).

6. RESULTS AND DISCUSSION

Impact of Training Data Size

The first set of experiments was devoted to the investigation of the size of the training dataset regarding the performance of the CNN. Table 1 summarizes the accuracy of classification achieved when the number of images was systematically varied across several experimental runs.

Table 1. Accuracy of the proposed CNN system with varying image counts.

Total Images	Training Images	Testing Images	Total Accuracy (%)
1,000	600	400	89.25
3,000	2,100	900	94.02
5,000	3,500	1,500	96.84
7,000	5,000	2,000	98.23

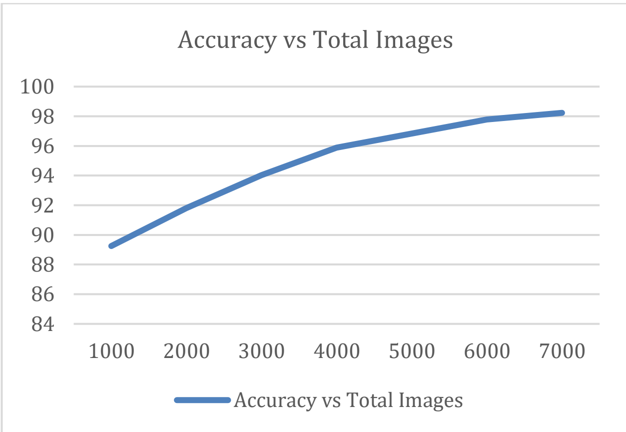

Figure 2. Accuracy vs Total Images.

The results indicate a high positive correlation exists between the amount of data and the performance of the machine learning models being analyzed. In general, as more images were used to train the models, the performance of these models improved; e.g., with 1,000 training images, the model achieved 89.25 % accuracy, while the model achieved 98.23 % accuracy with 7,000 training images. This suggests that CNNs are able to learn more complex and nuanced (discriminative) features by using large amounts of data. Consequently, large datasets can assist in the identification of complex defect patterns (e.g., crazing or rolled-in scale) through visual observation. Highest accuracies were reported for datasets that were approximately 70% of the entire dataset., which means that the opted training-to-testing split provides a good balance between learning capability and evaluation reliability. This goes in line with established principles in deep learning, where larger labeled datasets automatically lead to a higher generalization capability while reducing overfitting.

7. TRAINING AND TESTING ACCURACY

To further investigate how the model works, we conducted another experiment. This experiment looked at how gradually increasing the number of images affected both training and testing accuracy. The results of this experiment are shown in Tables 2 and 3.

The training accuracies shown in the table increase steadily as the size of the training set grows from 500 to 5,000 images. The training accuracies increase from 91.54% at 500 images to 98.36% at 5,000 images, which is indicative of effective feature extraction. The training accuracy curve also demonstrates a decrease in the degree of improvement, meaning that while the training accuracy will increase, the extent of the increase becomes increasingly smaller than the improvements shown earlier in the curve. This is often true of deep learning networks as they eventually reach a maximum capacity and performance will begin to be constant.

Number of Images	Training Accuracy (%)
500	91.54
1000	94.56
2000	95.23
3000	96.38
4000	97.15
5000	98.36

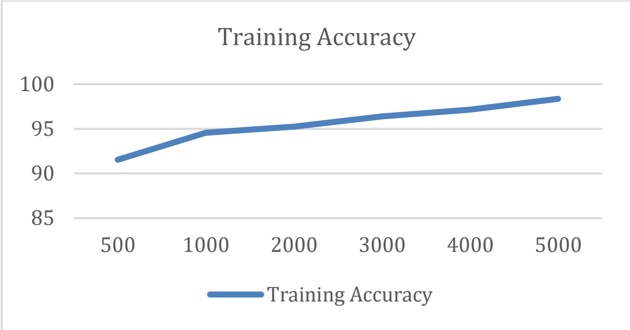

Figure 3. Training Accuracy.

Table 3. Testing accuracy trend.

Number of Images	Testing Accuracy (%)
500	91.94
700	93.42
900	94.73
1100	95.63
1300	96.21
1500	97.85

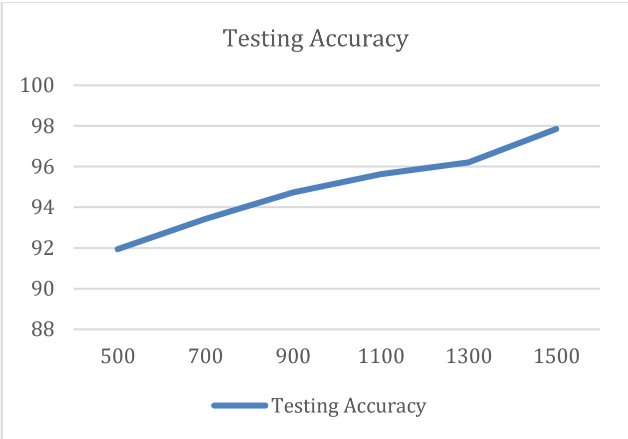

Figure 4. Testing Accuracy

The accuracy of the testing using datasets of 500 to 1,500 images is shown in Table 3. The testing accuracy improved from 91.94% to 97.85% over time, demonstrating that as more training data became available, the model improved its ability to generalise. Although the rate of improvement dropped somewhat at larger datasets, the upward trend remained unchanged.

The results show a very strong relationship between the accuracy achieved in both the training and testing phases. Further, a large quantity of training data contributed to improved internal learning by the model (training accuracy) and improved performance on samples previously unseen by the model (testing accuracy). The small difference between the training and testing accuracy indicates that the model Generalised well by not overfitting to the training dataset. Therefore, the CNN was able to detect important characteristics of steel surface defects without becoming overly dependent on the individual characteristics of the training images. Finally, the continual improvement in accuracy demonstrates how much benefit deep learning systems gain by being exposed to varied and large datasets; thus, emphasising the importance of providing large-scale training for industrial defect detection applications.

8. VISUAL PERFORMANCE

Qualitative assessment was undertaken to corroborate the model's visual recognition capabilities, in addition to numerical precision. The Convolutional Neural Networks (CNNs) demonstrated strong performance in classifying and locating surface imperfections with various types of surface defects, such as, inclusions, pitted surface and rolled-in scale defects, including complex patterns. In addition, the classification accuracy of the models remained high in the presence of noise.. Incorporating Gaussian noise effects had negligible effects on the overall stable system performance with respect to recognition ability; the effect of adding Gaussian noise (by using different levels of signal-to-noise ratio (i.e. 35, 25 and 15dB)) only slightly reduced the recognition accuracy. The ability of this model to continue functioning adequately under adverse conditions shows us that it can continue to operate well under common environmental conditions that exist in actual steel production facilities; for example, sensor noise, inconsistent lighting and inconsistent surface reflections. Since the model was able to operate normally in all these manufacturing issues demonstrates that the ability of the CNN architecture to be implemented in an industrially viable way; particularly for real-time inspection of products where the image conditions may be impractical or inconstant. Ultimately, visual and quantitative verification were provided by both forms of testing, concluding that the proposed defect detection using CNN is both efficient and dependable in meeting the high standards required for automated inspection of steel surfaces.

9. DISCUSSION

The findings of this investigation underscore the considerable promise of the proposed CNN-based steel defect detection system for practical industrial implementation. There is an identifiable trend across each of the test experiments conducted within the present project. As anticipated, the greater the size and diversity (heterogeneity) of the training dataset, the greater the effectiveness of the FAISS model was observed in:

- Recognizing relevant features from comparatively small datasets (e.g., using 600 images in the training dataset, the CNN achieved a classification accuracy of 89.25%);
- Producing a statistically significant increase in classification accuracy (a maximum accuracy level of 98.23% when trained on 5,000 or greater samples).

These results support the assertion that larger (more extensive) and more diverse datasets have a beneficial effect on the performance of deep learning models by improving the ability of the network to identify subtle differences between defect categories and reducing the occurrence of misclassification errors (over-fits). In addition, the fact that the training and testing accuracies were strongly correlated shows the robustness of the model (see Tables 2 and 3). The parallel increase in training and testing accuracy—as demonstrated in Figures 4 and 5—indicates that overfitting did not occur as the amount of training data increased. This is an especially important result for defect detection applications because, in many cases, defect categories are not predominately represented in the dataset, and therefore, the potential for overfitting is quite prevalent. Given that there is no meaningful difference between training and testing accuracy, the FAISS model generalizes well among all defect categories, which means the FAISS model can adequately classify previously unseen images. In conclusion, the conclusion is. Further insight into the adaptability of the convolutional neural network (CNN) was reached through an evaluation of its visual performance. CNNs were able to detect a number of different defect types while exhibiting high levels of detection accuracy even when subjected to external interference, such as Gaussian noise. The fact that the CNN can continue to achieve an acceptable level of accuracy when operating in environments where the signal-to-noise ratio (SNR) is 15 dB indicates that the model has the ability to perform reliably in situations characterised by significant variations in lighting, camera position and surface reflectivity (frequent problems in industrial inspection environments). Therefore, it is critical to assess the effectiveness of models developed in this manner using unsupervised pre-training techniques in environments with heterogeneous datasets and very complex discriminative features, as there will generally be limited control over imaging conditions on production lines where real-time production occurs. Thus, the results provide confirmation that a well-constructed CNN, developed with sufficient data and pre-processing methods, will provide defect detection accuracy and robustness that could be compared to human inspection within steel manufacturing. The model exhibits excellent generalisation capability, is very robust to noise, and is capable of distinguishing between a number of defect classes, all of which demonstrate that the model is able to support the implementation of automated inspection systems for use within the steel manufacturing environment. The next steps in this research area would be to determine and improve upon real-time implementation of the developed models, to investigate larger multi-environment datasets for the development of the models, and to consider hybrid architectures that combine the use of CNNs and transformers.

CONCLUSION

Research indicates that a Smart CNN-based defect detection system is effective for automating the inspection of steel plates. The proposed convolutional neural network (CNN) is designed to detect defects in steel plate assemblies through a series of examples or training data sets. The filters of the CNN are initialized with a sparse autoencoder, and then a backpropagation training algorithm trains the filters for defect detection. The final trained CNN system classified 98.23% of the inspected steel plates correctly using only 120 training examples; a clear improvement over traditional inspection processes. Furthermore, the research results indicate that using more training examples enhances defect detection capabilities. The use of CNN systems to detect defects offers an additional advantage because these systems allow for learning how to extract relevant features from inspection images without requiring prior knowledge of the necessary human visual parameters (e g., without having to preprocess the inspection images prior to processing). Furthermore, extensive evaluation of the CNN defect detection system, which used Gaussian noise and distorted images in conjunction with simulation testing, shows that the CNN defect detection system would operate effectively in industrial applications. Future work in this area could include real-time image acquisition systems to allow for the continued enhancement of the operation of the CNN defect detection systems for the real-time detection of multiple defect types by either developing a more advanced or hybrid CNN architecture, or creating an industrial version of the CNN defect detection systems for use in manufacturing. By implementing a Smart CNN defect detection system in manufacturing, examination time could be shortened through automated inspection systems, errors caused by manual input could significantly decrease, and overall improvement to the quality of products produced would be expected.

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