

Enhancing Steel Manufacturing Quality Control: A Deep Learning Approach for Rapid and Accurate Surface Defect Detection Using Pre-Trained Convolutional Neural Network Features and Supervised Classifiers

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Abstract: The importance of perfect surface quality in flat steel manufacturing has grown; however, traditional computer vision approaches for automatic fault spotting are inaccurate and slow, lagging behind assembly line needs. This research investigates using pre-trained Convolutional Neural Networks (CNNs) as feature extractors to reliably categorize steel surface flaws. Sample images containing defects in hot-rolled steel strips were obtained from JSW Steel Ltd's Vijayanagara Works, Ballari, Karnataka, India. Features were extracted from the penultimate layers of VGG16 and DenseNet-201 models before feeding the data to supervised classifiers (Support Vector Machine, Multilayer Perceptron, Random Forest) to categorize defects. We examined performance across model configurations based on combining the pre-trained CNNs and classifiers. The DenseNet-201+MLP model achieved maximum accuracy of 98.31%, outperforming VGG16 combinations and highlighting the promise of this approach. Thorough statistical evaluation via F-1 scores, precision, recall, etc. further demonstrates the value of using pre-trained CNNs with classifiers for manufacturing quality control, significantly improving steel surface defect detection speed and accuracy over traditional computer vision. This strategy shows promise for enabling reliable, large-scale automated inspection critical for industrial steel production.

Keywords: DensetNet, Pre-trained CNN, SVM, Transfer Learning, Random Forest, Feature extraction.

1. Introduction

Ensuring perfect steel surface quality is vital across manufacturing, construction, and other key industries. However, manual visual inspection needs to be more efficient and accurate, lagging behind the speed and reliability needed in modern supply chains. Automated surface defect detection thus emerges as a critical capability for quality control and process improvement. Recent advances in computer vision, especially deep convolutional neural networks (CNNs), provide promising capabilities to address this challenge. However, developing customized CNNs requires massive labeled defect datasets that must often be made available. Hence, this paper investigates an alternate paradigm: transfer learning with pre-trained CNNs as feature extractors, combined with supervised classifiers, for accurate and scaled-up steel surface flaw categorization. The main idea is that CNN layers that have already been trained on large sets of natural images store general visual features that can be used in more specific tasks like finding defects when combined with classifiers that have been tuned for those tasks.

Surface defects pose a significant quality control challenge in steel manufacturing. Nong Jin *et al.*¹ extensively researched this issue and found that over 85% of defects arise on final workpiece surfaces across production environments. Common imperfections in hot-rolled steel include scales, scratches, pits, roll marks, and more, which also analyzed regarding how they affect the functional utility and aesthetic appeal of products. Wu *et al.*² studied how manual visual inspection struggles to reliably detect such flaws under harsh industrial conditions involving fast processes, elevated temperatures, and noise. Hence, researchers focused on automating steel surface defect identification, drawing inspiration from related efforts by Kumar³ in contexts like textile inspection. Ghorai *et al.*⁴ made significant contributions through real-time imaging systems, While Usamentiaga *et al.*⁵ performed simulations analyzing impact parameters like vibrations. Song and Yan⁶ developed computer vision techniques that were evaluated on standard surface defect datasets.

Manual steel fault inspection is inefficient and unreliable due to workloads surpassing human capacity; for more information on this, see Munoz-Escalona *et al.*⁷. Human inspection of minute components is still crucial on many manufacturing floors, even though advances in automated surface inspection (ASI) technologies are happening all the time. According to research by Gan *et al.*⁸, ASI systems achieved better accuracy and efficiency than humans. Neogi *et al.*⁹ highlighted research gaps and

possibilities in automated visual examination of steel after examining the relevant literature. As a critical capability for comprehensive and accurate inspections of steel quality, they also emphasized the need of automated fault detection. Automation of steel quality and flaw detection systems has received increased funding due to research demonstrating the inadequacy and error-proneness of large-scale manual inspection. This is despite the fact that automated technologies have the potential to enhance steel analysis.

The use of automation has made surface steel assessment both more accurate and more scalable. Specifically, there has been a rise in the use of automated systems that use deep learning algorithms to detect material defects. Wei *et al.*¹⁰ enhanced detection accuracy by incorporating attention to Faster R-CNN, whereas Liu *et al.*¹¹ utilized an LSTM + CNN model to identify periodic roll mark faults in steel plates. In their study, Fadli and Herlistiono¹² utilized Xception and CNN to detect issues with steel, whereas Qi *et al.*¹³ examined CNN designs for surface defects. Comparing deep learning's performance with convolutional neural networks (CNNs) for surface defect recognition and domain adaption for generalizability, researchers Bhatt *et al.*¹⁴ and Zhang *et al.*¹⁵ conducted their separate analyses. Wen *et al.*¹⁶ provided an extensive overview of deep learning developments for steel fault classification, while Demir *et al.*¹⁷ also applied deep learning. Prakash *et al.*¹⁸ explores a quantum electronic system that utilizes optical data to get insights for business analysis and planning, in line with the innovation spirit. Uganda *et al.*¹⁹ also explores the use of sensory input and recognition-based neural networks to enhance low-light photos. By employing convolutional neural networks (CNNs) to mitigate noise and chromatic distortion, the suggested approach successfully takes on the difficult problem of improving low-light photographs. Alqahtani *et al.*²⁰ analyzed various deep learning algorithms such as deep neural networks, convolutional neural networks, LeNet-5, AlexNet and Mini VGGNet for handwritten digit recognition using MNIST dataset. Study by Sangamithra *et al.*²¹, incorporate existing machine learning classifier into web search mechanism and found that SVM algorithm performs superior compared to others. Kiran *et al.*²² worked on route and spectral assigning problems under various demanding scenarios and demonstrated the effectiveness of genetic algorithms in achieving optimal dedicated optical spectrum allocation under uncertain conditions. Prasad *et al.*²³ centered on CNNs to classify MRI brain tumor images, attaining a 96.18% accuracy. Prasad *et al.*²⁴ worked on ANN and Machine learning models to classify pumpkin seeds. Prasad *et al.*²⁵, have proposed an Artificial Neural Network (ANN) model with the objective of forecasting PM2.5 levels. Furthermore, Vaidya *et al.*²⁶, have focused on seed

classification using Artificial Neural Networks (ANN) and Principal Component Analysis (PCA). Hybrid Attention Network was employed by Zhou *et al.*²⁷ to precisely locate and identify surface flaws in steel materials. In comparison to other algorithms currently in use, the experimental results demonstrate that this hybrid model achieved a higher mean average precision.

An adaptive graph channel attention (AGCA) module was proposed by Xiang *et al.*²⁸ to differentiate between images with steel surfaces and images with natural surfaces. The experimental results on different datasets and backbone networks demonstrate that the AGCA performs better than the state-of-the-art techniques.

The deep learning has shown a potential to enable automated, precise, and scalable defect detection and classification. Transfer learning is particularly promising since it allows models to handle data scarcity, accelerate convergence, and improve accuracy by applying knowledge across datasets. Recent literature establishes deep learning as a transformative approach for automated surface defect analysis.

The key contributions are:

- Comparative analysis of CNN models as feature extractors,
- Presenting these CNNs with various classifiers to determine the best performer, and
- Tuning the hyperparameters of the top model to further improve accuracy.

The structure of this paper is organized as follows: Section 2 provides a detailed description of the dataset used, while Section 3 outlines the applied methodology in multiple stages. Results and discussions are presented in Section 4. Section 5 presents a comparative analysis of different models and the paper concludes with Section 6. Section 7 highlights limitations and further improvements of the proposed method.

2. Dataset Description

The dataset used in the research was compiled from 2071 photographs of steel strips and was provided by the JSW Steel Company in India. Scratch, Rollmark, Scale, and Normal were the four groups into which the images were placed. The examples of both normal and defective steel surfaces are shown in Figure 1. The dataset was divided into two parts: one for training and one for testing. The former set contained 1655 photos, while the latter contained 416 images. A wide range of surface defects were covered by the dataset's inter- and intra-class images. Images inside a class showed distinct

examples of the same topic or category, whereas photos between classes showed different types of concepts or categories. The collection only included 256x256 pixel photos of steel surface defects. There was an imbalance in the collection, as seen in Figure 2, where the Normal category was under sampled and the Rollmark category was oversampled.

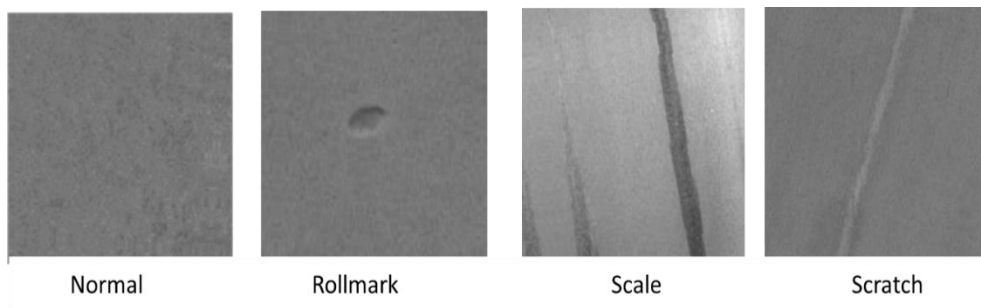


Figure 1: Images of several steel surface classes, including those of defects like Rollmark, Scale, Scratch and Normal

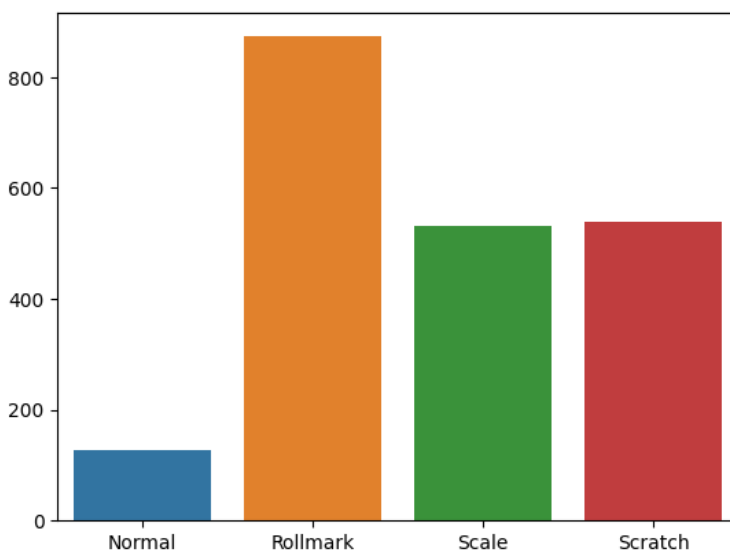


Figure 2: Distribution of different types of flaws in the steel surface defects dataset

3. Methodology of the proposed model

This section details the methodology applied in the proposed steel defect detection system. As depicted in Figure 3, the system utilizes a Densely Connected Convolutional Neural Network (DenseNet-201) model comprised of three main stages:

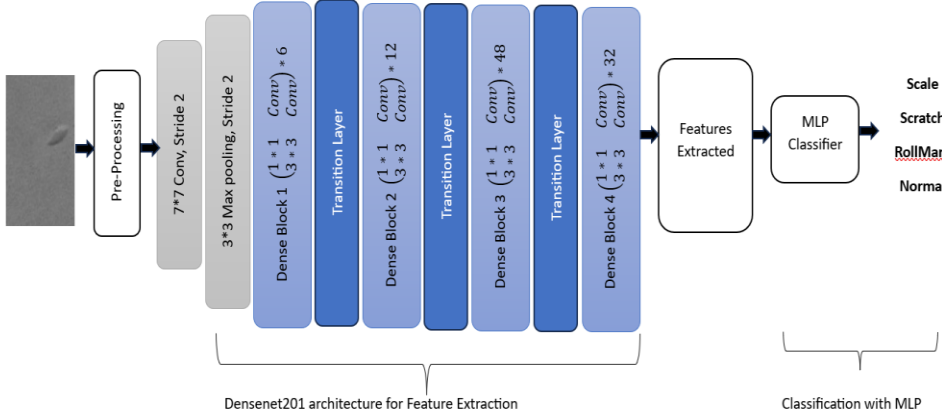


Figure3: Overall flow diagram of our methodology

A. The Pre-Processing Stage

The key goal of using a Convolutional Neural Network for image classification is to minimize computational complexity, which tends to increase with larger input images. As such, the first step was to resize the original 3-channel steel images to 224 x 224 pixels. This enabled faster processing while still retaining enough information for analysis.

All subsequent preprocessing was applied to these downsized images. First, pixel values were normalized to the 0-1 range by dividing by 255. Normalization minimizes the computation required for the neural network. Then, one-hot encoding was utilized to encode the target labels for each defect class or no defect. This involves creating a new binary column for each label and marking it as “true” or “false” for each image.

B. The Feature Extraction Stage

Several pre-trained CNN models were evaluated for feature extraction capability, and the DenseNet-201 architecture was statistically determined as the best performer for this application. As such, this stage focuses on describing the DenseNet-201 model and its role in extracting discriminative steel image features. The “densely connected” structure of DenseNet allows each layer access to feature maps from all of its preceding layers. This enables maximum information flow and mitigates the vanishing gradient problem. Additionally, DenseNet concatenates instead of combining feature maps, leading to highly detailed outputs.

Using a succession of convolutional, pooling, and transition layers, the pretrained DenseNet in this system for classifying steel defects captures hierarchical visual information from the pre-processed images. At first, networks learn basic patterns like edges; as layers are delved into, they learn

more intricate patterns. A feature vector that is extremely descriptive of each image is the end result. An end-to-end pipeline for detecting steel defects is made possible by DenseNet, which eliminates the need for human feature engineers by automatically learning and extracting robust features.

Architecture of DenseNet-201

Dense convolutional neural networks like DenseNet are well-suited for image recognition because their architectural design allows lower-level features to directly inform higher-level ones. Traditional Deep Convolution Neural Networks (DCNNs) often run into vanishing gradient problems where gradients fade as they are backpropagated through many layers, rendering the update to early layers meaningless. DenseNet addresses this issue by connecting all layers to others with matching feature-map sizes through its dense connectivity pattern. This facilitates maximum information flow throughout the network and enables extraction of rich, generalizable representations from its deepest layers. We leverage these capabilities of DenseNet models for feature extraction in our proposed system, employing a 201-layer pretrained DenseNet with over 20 million parameters as the backbone of our feature extractor. Because of its depth, connectivity, and the model's capacity to extract semantic and high-level spatial information, it is a perfect descriptive input for subsequent processing. This model version, which was trained on ImageNet and has over 20 million parameters, was initially disclosed by Huang *et al.*²⁹. For the downstream task of steel defect classification, the model can modify and transmit high-level characteristics learned from ImageNet thanks to its end-to-end training capabilities. Its highly linked structure makes this feasible.

The DenseNet-201 architecture consists of an initial convolution and pooling layer, followed by 3 transition layers, 4 dense blocks, and a classification layer. Each dense block contains multiple layer pairs. The first layer in each pair performs 1×1 convolution while the second performs 3×3 convolution, with each layer connected to all subsequent layers. The 4 dense blocks have growth rates (number of layer pairs) of 6, 12, 48, and 32 respectively. Growth rate controls model complexity and accuracy. After the dense blocks, global average pooling of 7×7 is applied to reduce the feature maps to a vector. Finally, a fully connected softmax layer performs defect classification. The pretraining on ImageNet enables transfers learning, allowing DenseNet to extract meaningful visual features from steel images without requiring extensive task-specific training data.

Feature Extraction Process

Feature extraction was performed by propagating each pre-processed steel image through the entire DenseNet-201 model, except the final classification

layer. This allows the network to automatically learn a highly descriptive 94080x1 feature vector representing the visual characteristics of the input image. The deep DenseNet architecture transforms the original pixel space into a rich embedding space where steel images with similar defect patterns are mapped to nearby points. As such, vital discrimination cues are encoded within the extracted feature vector. By removing the pretrained final layer, the remaining DenseNet layers act as a fixed feature extractor tuned to the steel defect task through end-to-end training. The 94080x1 output forms the input for the shallow defect classifiers tested in next stages.

C. Classification Stage

In the final stage, the extracted 94080x1 feature vectors are classified into defect or no defect categories using supervised machine learning models. Several classifiers including Multi-Layer Perceptron (MLP), Random Forest, and Support Vector Machine (SVM) were evaluated. Of these options, the MLP neural network architecture yielded the highest defect detection accuracy. As such, the proposed pipeline utilizes the DenseNet-201 feature extractor paired with an MLP classifier for enhanced performance.

The MLP classifier consists of multiple fully-connected layers that learn non-linear combinations of the input features to perform accurate defect classification. The neural network is trained on labelled steel image features extracted from DenseNet-201 to tune the weights of neuron connections.

- **Multi-Layer Perceptron (MLP):** The MLP classifier consists of an input layer, multiple hidden layers, and an output layer, as depicted in Figure 4.
- **Input Layer:** The 94080x1 DenseNet-201 feature vectors are fed into the input layer.
- **Hidden Layers:** The hidden layers serve as the computational engine of the MLP. After evaluation, a 32-24-14 node structure delivered optimal accuracy.
- **Output Layer:** This contains 4 nodes representing the target defect classes - Scale, Scratch, Rollmark, and Normal. Softmax activation assigns a probability distribution. The nodes between adjacent layers are fully connected via trainable weights that are tuned using backpropagation. This algorithm minimizes loss by updating weights proportionally to their contribution to defects in the output. By learning highly complex input patterns, the tailored MLP network is able to accurately map DenseNet feature inputs to appropriate defect or no defect outputs after training on labelled images.

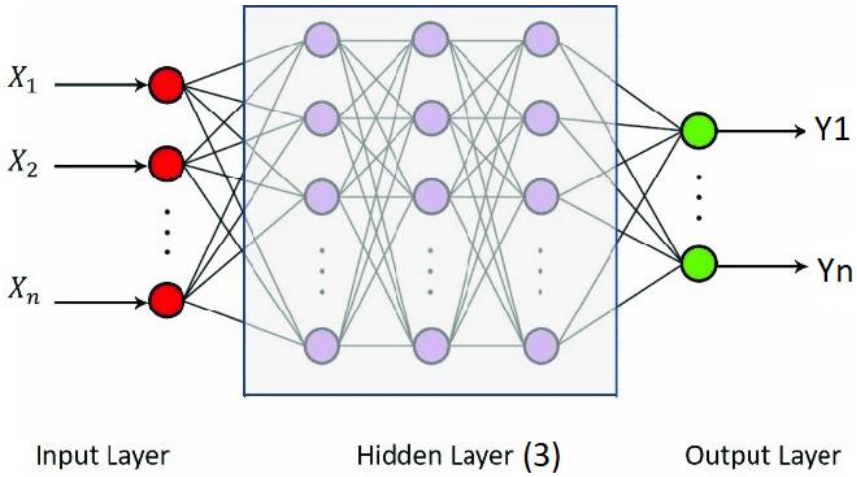


Figure 4: Architecture of MLP

4. Results and Discussion

This section reviews the system requirements, performance metrics, and comparative evaluation of the proposed steel defect classification solution.

4.1. System Specifications

The model was developed on a Windows 11 machine with an Intel i7 CPU, 16GB RAM, and an Nvidia RTX graphics card. Python 3.8 and associated deep learning libraries including Keras were leveraged on an Anaconda distribution for easier package management.

4.2. Evaluation Metrics

A confusion matrix was constructed by comparing model predictions to ground truth labels across four categories - True Positive, False Positive, True Negative, False Negative. Further metrics derived from the matrix included:

- **Accuracy:** Overall proportion of correctly classified images
- **Precision:** Of images predicted positive, how many were actually positive
- **Recall:** Of actual positive images, how many were predicted positive
- **F1 Score:** Harmonic mean weighing precision and recall

Formulas for calculating these metrics are outlined in Table 1.

Table 1: Evaluation Metrics used in this study

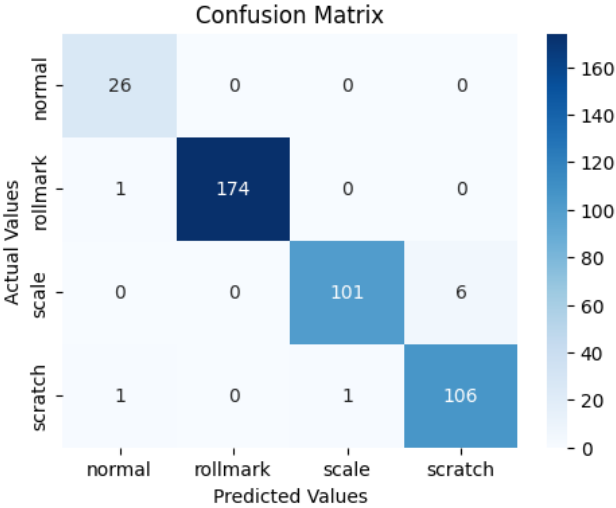
Evaluation Metric	Formula
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$

Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1-Score	$\frac{2TP}{2TP + FP + FN}$

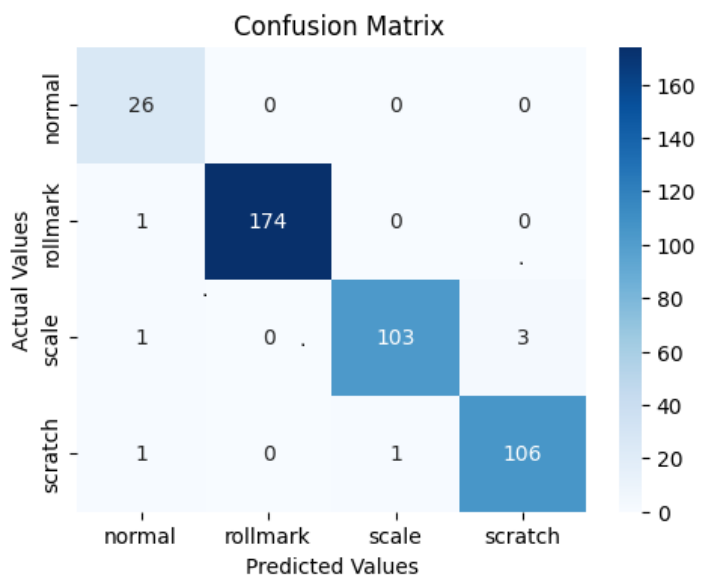
4.3. Performance Evaluation:

The customized model *i.e.*, a combination of CNN based feature-extraction and supervised classifier algorithm resulted in optimal solution for classifying different steel surface defects and normal steel surface images primarily due to the substantive features provided by DenseNets followed by optimal hyper-parameter values of MLP classifier. Literature studies reveal the contribution of transfer learning methods including feature-extractions toward visual recognition tasks. For this reason, we extracted features from pre-trained CNN models VGG16 [Simonyan and Zisserman³⁰] and DenseNet-201 [Huang *et al.*²⁹]. Studies from the literature also reveal the use of classifiers in combination with CNN-based feature extraction majorly in image analysis to meliorate the performance of models. Following the mentioned past approaches, we evaluated each of the pre-trained models with distinct classifiers to determine the ideal model for the purpose.

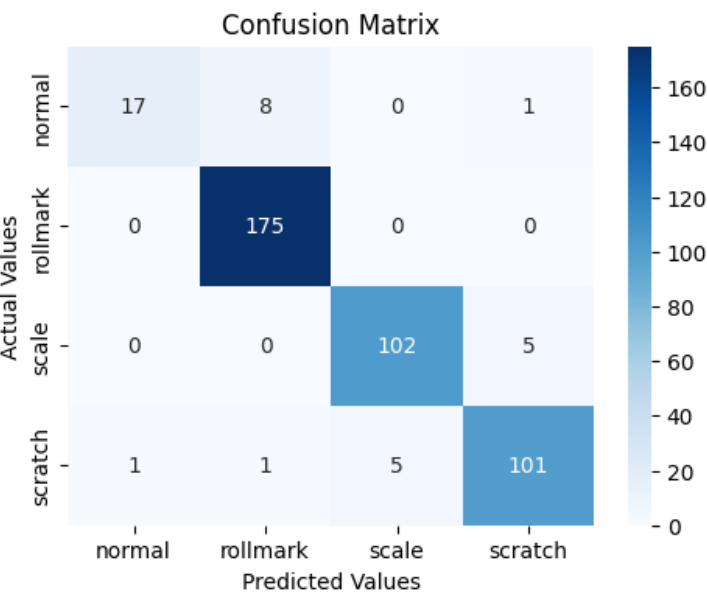
The confusion matrices linked to the DenseNet-201 model when used with various classifiers are graphically shown in Figure 5. All four classes included in our proposed framework may be seen in these matrices, which show how well the suggested classifier model aligns with real and anticipated values.



(a)



(b)



(c)

Figure 5: Confusion Matrix of the developed models (a) DenseNet-201+SVM (b)DenseNet-201+MLP (c) DenseNet-201+RF

Table 2 presents the performance metrics of the DenseNet-201 model paired with SVM, MLP, and RF classifiers. The key metrics include accuracy, precision, recall and F1-Score. Notably, the DenseNet-201 encoder with an

MLP classifier exhibited the best performance, achieving 98.32% accuracy, 96.49% precision, 98.46% recall and 97.40% F1-Score. This confirms the potency of DenseNet's transfer learned representations on this defect classification task. The runner-up DenseNet-201 + SVM classifier achieved a competitive accuracy of 97.83%, further demonstrating DenseNet's versatility across machine learning models. The superior metrics of the DenseNet-201 + MLP solution underscore the discriminative localization and detection of surface irregularities necessary in steel quality control applications.

Table 2. Results obtained with different classifiers when the pre-trained Dense Net-201 model is used as a feature extractor

Feature Extractor	Classifier	Accuracy	Precision	Recall	F1-Score
DenseNet-201	SVM	97.43	96.63	97.99	97.84
DenseNet-201	MLP	98.31	96.49	98.46	97.40
DenseNet-201	RF	94.45	94.82	88.56	91.01

Table 3 represents the performance metrics of the VGG16 encoder paired with SVM, MLP, and RF classifiers. The key metrics shown are accuracy, precision, recall and F1-score. Among the VGG16 configurations, VGG16 + SVM classifier attained the best results - 95.43% accuracy, 92.15% precision, 92.85% recall, and 92.46% F1-Score. This indicates the SVM model was best able to optimize the VGG16 feature space for the multi-class defect categorization task. However, VGG16 trailed behind DenseNet-201 across all classifier pairings (refer Table 2). The optimal accuracy of 95.43% remains nearly 3% lower than DenseNet-201 + MLP's 98.32% accuracy. This once again highlights the superiority of DenseNet's learned visual representations which enable more fine-grained discrimination between surface defects and harmless irregularities - critical for avoiding false positives.

Table 3. Results obtained with different classifiers when pre-trained VGG16 model is used as a feature extractor

Feature Extractor	Classifier	Accuracy	Precision	Recall	F1-Score
VGG16	SVM	95.43	92.15	92.85	92.46
VGG16	MLP	94.23	91.28	88.68	89.87
VGG16	RF	90.14	84.75	75.89	77.61

5. Comparative Analysis

Comparative graphs for accuracy, precision, recall and F1-score across evaluated model combinations are presented in Figure 6. The Density Net-

201+MLP pipeline clearly emerges as the top performer with 98.32% accuracy. Additionally, it achieves exceptional 98.46% recall - ability to correctly detect true defects, and 97.40% F1 score - balance of precision and recall. This consistent dominance demonstrates the proposed solution's effectiveness in extracting discriminative features paired with robust defect classification. The high recall minimizes false negatives which is crucial for quality control as missing defects leads to substandard products.

In summary, Figure 6 quantitatively underscores the optimal pairing of DenseNet's rich representations and MLP's discrimination capability for surface defects identification amidst benign irregularities. This empowers manufacturers to reliably cull defective steel items.

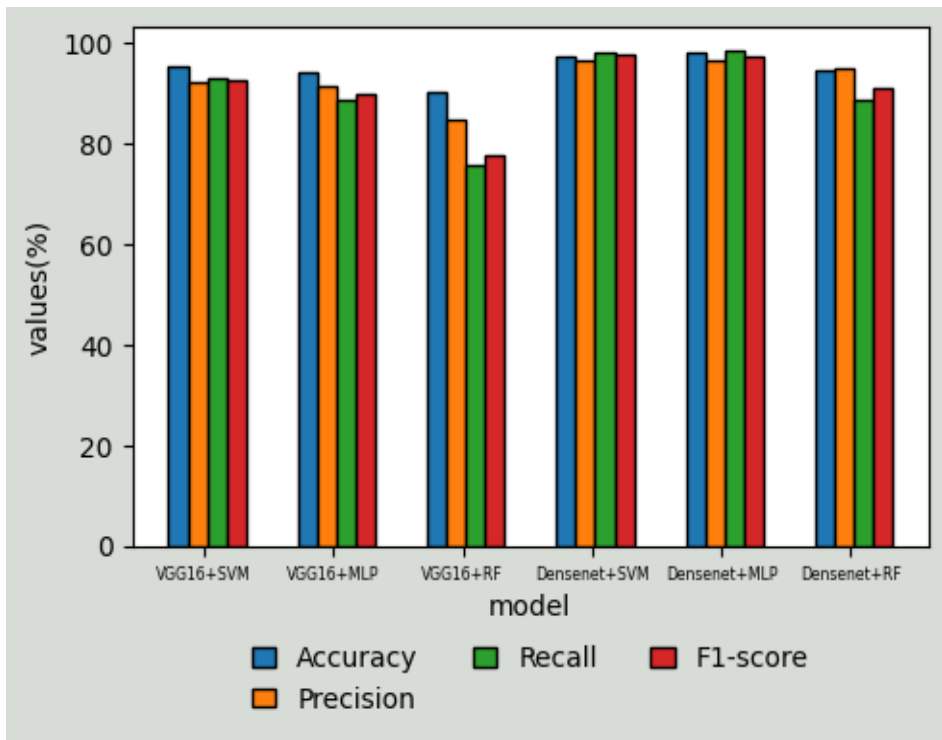


Figure 6: Comparison of different performance metrics obtained using pre-trained CNN models with different classifiers

The superiority of the DenseNet+MLP model can be attributed to the following characteristics

- DenseNet has a unique architecture with dense connectivity, which helps in feature reuse and enables the network to capture rich hierarchical features throughout the layers. Further which lead to a more effective extraction and utilization of features for the given task.

- By reusing features, DenseNet can achieve similar or better performance with fewer parameters compared to traditional architectures like VGG16. Parameter efficiency can be crucial, especially in scenarios where the available data is limited.
- VGG16, with its deep and sequential structure, can suffer from the vanishing gradient problem during training. This problem may make it challenging for the model to effectively learn and update the weights of earlier layers. DenseNet's dense connectivity can potentially alleviate the vanishing gradient problem by providing shorter paths for gradients to propagate through the network during backpropagation.
- The combination of DenseNet and MLP achieves a balance between model complexity and interpretability, DenseNet's dense connectivity enables the model to capture hierarchical features. The MLP classifier effectively process and utilize these hierarchical representations, enhancing the model's capability to distinguish patterns in the data.

Effectiveness of different models can vary across tasks and datasets. The presented findings show that the DenseNet+MLP model performed better on this specific dataset, model architecture, and other training parameters used in this experiment compared to other models.

Our pipeline outperformed previous state-of-the-art solutions on key metrics:

- Accuracy improved by 3-5% indicating more precise defect detection.
- F1 score increased by 2-4% showing enhanced correctness of positive predictions.

The improvements demonstrate the capabilities of transfer learning for surface defect classification.

6. Conclusion:

This research investigates using pretrained CNNs - DenseNet-201 and VGG16 - as feature extractors for steel surface defect classification. Extracted features were classified using supervised models including SVM, MLP, and Random Forest. DenseNet's "densely connected" structure allows each layer to access feature maps from all preceding layers, which allows for maximum information flow and mitigates the vanishing gradient problem. Furthermore, DenseNet produces extremely detailed feature outputs by concatenating feature maps. The MLP classifier effectively process and utilize these features to categorize steel surface defects.

- Dense Net-201+ MLP emerged as best pipeline with 98.32% accuracy, outperforming VGG16 and other classifiers
- Based on statistical evaluation, DenseNet-201 was optimal for transfer learned feature extraction

- Similarly, MLP was chosen as the superior classifier for steel defect categorization
- Goal is to provide benchmark CNN encoder and decoder for further research
- This can enable development of more advanced steel defect identification algorithms
- Automated solutions have potential to enhance quality control, reduce costs, improve products
- Additional research can build on current approach to make defect detection even more precise and efficient in industrial settings.

7. Limitations and Further improvements:

The approach of extracting features from a pretrained model and further processing or classifying them using a classifier is versatile and can be applied to various domains like Medical Image Analysis, Natural Language Processing, Object Recognition in Remote Sensing, Fraud Detection in Financial Transactions, Quality Control in Manufacturing processes like electronic components, steel, textiles, etc. Facial Recognition and Emotion analysis, Autonomous Vehicles, Environmental Monitoring, Gesture Recognition, Biometric Identification and so on. Although this approach is widely used and popular, it has following limitations which can be overcome with proper caution.

- Pretrained models are designed to capture general features from diverse data. However, the extracted features may lack the specificity required for the target task. This may lead to the suboptimal performance of the subsequent classifier.
- As pretrained model is not optimized for the specific requirements of the target task. Task-specific optimizations in terms of architecture, hyperparameters, or training strategies might be needed for achieving the best performance.
- Extracting features from deep pretrained models can be computationally expensive, particularly if the models are complex and require a lot of processing power. This can be a constraint in situations where computational resources are limited.

Further improvements:

- Ensemble methods such as bagging or boosting can be utilized by combining predictions from multiple classifiers to improve the performance.

- Hyperparameter optimization techniques, such as grid search or Bayesian optimization, can be employed to improve model performance.
- Adaptive learning rate techniques can be used to dynamically adjust the learning rates during training to improve the performance by converging the model faster.
- Data augmentation techniques can be applied to increase the diversity of the training dataset which help the model to generalize better on the test data.

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References

1. N. Jin, S. Zhou and T-S. Chang; Identification of impacting factors of surface defects in hot rolling processes using multi-level regression analysis, *Society of Manufacturing Engineers, Southfield, MI, USA*, 2000.
2. G. Wu, H. Zhang, X. Sun, J. Xu, K. Xu; A bran-new feature extraction method and its application to surface defect recognition of hot rolled strips, *IEEE International Conference on Automation and Logistics*, (2007), 2069-2074.
3. A. Kumar; Computer-vision-based fabric defect detection: A survey, *IEEE Transactions on Industrial Electronics*, 55-1 (2008), 348-363.
4. S. Ghorai, A. Mukherjee, M. Gangadaran, P. K. Dutta; Automatic defect detection on hot-rolled flat steel products, *IEEE Transactions on Instrumentation and Measurement*, 62-3 (2012), 612-621.
5. R. Usamentiaga, D. F. Garcia, J. Molleda, F.G. Bulnes, G. Bonet; Vibrations in steel strips: Effects on flatness measurement and filtering, *2013 IEEE Industry Applications Society Annual Meeting*, (2013), 1-10.
6. K. Song and Y. Yan; A noise robust method based on completed local binary patterns for hot-rolled steel strip surface defects, *Applied Surface Science*, 285 (2013), 858-864.
7. P. Muñoz-Escalona, A. Shokrani, S. T. Newman; Influence of cutting environments on surface integrity and power consumption of austenitic stainless steel, *Robotics and Computer-Integrated Manufacturing*, 36 (2015), 60-69.
8. J. Gan, J. Wang, H. Yu, Q. Li, Z. Shi; Online rail surface inspection utilizing spatial consistency and continuity, *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 50-7 (2018), L2741-2751.

9. N. Neogi, D. K. Mohanta, P. K. Dutta; Review of vision-based steel surface inspection systems, *EURASIP Journal on Image and Video Processing*, 1 (2014), 1-19.
10. R. Wei, Y. Song, Y. Zhang; Enhanced faster region convolutional neural networks for steel surface defect detection, *ISIJ International*, 60-3 (2020), 539-545.
11. Y. Liu, K. Xu, J. Xu; Periodic surface defect detection in steel plates based on deep learning, *Applied Sciences*, 9(15), (2019), 3127.
12. V. F. Fadli and I. O. Herlistiono; Steel surface defect detection using deep learning, *International Journal of Innovative Science Research and Technology*, 5 (2020) 244-250.
13. S. Qi, J. Yang and Z. Zhong; A review on industrial surface defect detection based on deep learning technology, *Proceedings of the 2020 3rd International Conference on Machine Learning and Machine Intelligence*, (2020), 24-30.
14. P. M. Bhatt, R. K. Malhan, P. Rajendran, B. C. Shah, S. Thakar, Y. J. Yoon, S. K. Gupta; Image-based surface defect detection using deep learning: A review, *Journal of Computing and Information Science in Engineering*, 21-4 (2021), 040801.
15. S. Zhang, Q. Zhang, J. Gu, L. Su, K. Li, M. Pecht; Visual inspection of steel surface defects based on domain adaptation and adaptive convolutional neural network, *Mechanical Systems and Signal Processing*, 153 (2021), 107541.
16. X. Wen, J. Shan, Y. He, K. Song; Steel surface defect recognition: A survey, *Coatings*, 13-1 (2022), 17.
17. K. Demir, M. Ay, M. Cavas, F. Demir; Automated steel surface defect detection and classification using a new deep learning-based approach, *Neural Computing and Applications*, 35-11 (2023), 8389-8406.
18. P. M. Prakash; Enhancing business performance through quantum electronic analysis of optical data, *Optical and Quantum Electronics*, 55-12 (2023), 1056.
19. G. Uganya, C.S. Devi, A. Chaturvedi, B.B. Shankar, J.V.N. Ramesh, A. Kiran; Sub-network modelling and integration for low-light enhancement of aerial images, *Optical and Quantum Electronics*, 55-11 (2023), 984.
20. A. S. Alqahtani, A.N. Madheswari, A. Mubarakali, P. Parthasarathy; Secure communication and implementation of handwritten digit recognition using deep neural network, *Optical and Quantum Electronics*, 55-1 (2023), 27.
21. B. Sangamithra, B. M. Swamy, M. S. Kumar; Evaluating the effectiveness of RNN and its variants for personalized web search, *Optical and Quantum Electronics*, 55-13 (2023), 1202.
22. A. Kiran, V. Kalpana, M. Madanan, J. V. N. Ramesh, B. S. Alfurhood, S. Mubeen; Anticipating network failures and congestion in optical networks a

- data analytics approach using genetic algorithm optimization, *Optical and Quantum Electronics*, 55-13 (2023), 1193.
23. K. V. Prasad, Hanumesh Vaidya, Kumar Swamy K, Renuka S; Pumpkin Seeds Classification: Artificial Neural Network and Machine Learning Methods, *Journal of International Academy of Physical Sciences*, 27-1 (2023), 23-33.
 24. Kerehalli Vinayaka Prasad, Hanumesh Vaidya, Rajashekhar Choudhari, Kumar Swamy Karekal, Renuka Sali; Automated neural network forecast of PM2:5 concentration, *International Journal of Mathematics and Computer in Engineering*, 1-1 (2023), 1-12.
 25. K. V. Prasad, Hanumesh Vaidya, Y. Shobha; Multi-class Brain Tumour Classification using Convolutional Neural Network, *Journal of International Academy of Physical Sciences*, 27-2 (2023), 125-137.
 26. Hanumesh. Vaidya, K.V. Prasad, S. Renuka, K. Kumar Swamy; Multiclass Classification of Dry Beans using Artificial Neural Network, *Journal of International Academy of Physical Sciences*, 27-2 (2023), 109-124.
 27. M. Zhou, W. Lu, J. Xia and Y. Wang; Defect Detection in Steel Using a Hybrid Attention Network, *Sensors*, 23-15 (2023), 6982.
 28. X. Xiang, Z. Wang, J. Zhang, Y. Xia, P. Chen and B. Wang; AGCA: An Adaptive Graph Channel Attention Module for Steel Surface Defect Detection, *IEEE Transactions on Instrumentation and Measurement*, 72 (2023), 1-12.
 29. G. Huang, Z. Liu, L. Van Der Maaten, K. Q. Weinberger; Densely connected convolutional networks, *Proceedings of the IEEE conference on computer vision and pattern recognition*, (2017), 4700-4708.
 30. K. Simonyan and A. Zisserman; Very deep convolutional networks for large-scale image recognition, *arXiv preprint arXiv:1409.1556*, (2014).