Automating Steel Defect Detection Using Deep Learning and Computer Vision

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ABSTRACT

This project explores the application of deep learning in automating the detection and classification of steel surface defects, a critical task in industrial quality control. Traditional manual inspection methods are prone to error and inefficiency, especially in high-volume production settings. To address these challenges, a ResNet50 deep learning model was fine-tuned on a dataset of steel defects, including types such as crazing, inclusion, scratches and so on. The project used an organised methodology that included gathering data, preparing it, training the model, and deploying it. Data augmentation techniques were applied to handle class imbalance, and the model was trained and evaluated using metrics like accuracy, precision, recall, and confusion matrices. The final model was integrated into a Streamlit-based web interface that allows real-time defect classification, providing operators with a user-friendly tool to enhance productivity and quality assurance. The results demonstrate the model's capability in accurately identifying various defect types, suggesting that deep learning can significantly improve efficiency in steel manufacturing. Future research will concentrate on improving real-time processing and broadening the model's applicability in other industrial settings.

Keywords: Steel defect detection, Deep learning, ResNet50, Data augmentation, Streamlit, automated quality control,

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DEDICATION

I dedicate this project to School of Science and Technology, Pan-Atlantic University, which has provided me with the knowledge and skills necessary to pursue this endeavor, and to iSEND, whose innovative approach and support during my internship inspired this work. Additionally, I dedicate this to my family and friends for their constant encouragement and unwavering belief in my abilities.

STUDENT'S DECLARATION

I have read and understood the School of Science and Technology Policy on plagiarism. I declare that this project is my own work and that all sources are fully referenced. I also declare that I have not submitted this work for any other purpose.

Makuochukwu Alex Ezeonye

23120133009

Date: October 21st, 2024.

CERTIFICATION

I certify that this work was carried out by Makuochukwu Alex Ezeonye with matriculation number 23120133009, in the School of Science and Technology, Pan-Atlantic University, under my supervision.

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CHAPTER ONE: INTRODUCTION

1.1 Background to the Study

Steel production is a critical component of many industries, including construction, automotive manufacturing, aerospace, and shipbuilding. Its strength, versatility, and cost-effectiveness make it an essential material for infrastructure and technological advancements. However, the quality of steel directly impacts its performance and durability. Surface defects such as crazing, pitting, rolled-in scale, and scratches can compromise structural integrity, leading to costly recalls, reduced lifespan of products, and in severe cases, catastrophic failure (Zhang et al., 2020). The detection and classification of these defects are therefore crucial to maintaining high standards in steel production.

Traditionally, defect detection in steel surfaces has been performed manually by trained human inspectors. This method is not only labor-intensive but also prone to inconsistencies due to human fatigue, subjectivity, and the limitations of visual inspection. As a result, many defects may go unnoticed or be inaccurately classified, leading to inefficiencies in the production process and suboptimal quality control (Kumar et al., 2021). Additionally, with the increasing scale of production and the demand for higher quality materials, manual inspection methods have proven to be insufficient in meeting the speed and precision required by modern manufacturing.

With the rise of Industry 4.0, which emphasizes the integration of smart technologies into manufacturing processes, there has been a growing interest in automating quality control procedures. Deep learning and computer vision are two of these technologies that have demonstrated exceptional promise in automating the identification and categorisation of defects in steel surfaces. By using machine learning algorithms, large datasets of defect images can be processed to train models that can recognize patterns and classify defects with high accuracy (He et al., 2016). These automated systems not only reduce the reliance on human inspectors but also improve consistency and speed, enabling real-time feedback during the production process.

Deep learning architectures such as ResNet50 and MobileNet have proven to be highly effective in image recognition tasks, including defect detection in industrial settings. In specifically, ResNet50 is a popular convolutional neural network (CNN) that was created to solve the problem of disappearing gradients in deep networks and increase the accuracy of image classification tasks (He et al., 2016). By utilizing these deep learning models, manufacturers can significantly enhance the precision of defect detection and classification, leading to better quality control and cost savings. The integration of these systems into the steel manufacturing process represents a significant advancement in industrial automation and smart manufacturing.

The goal of this research is to use deep learning techniques to create a system that can automatically detect and classify defects on steel surfaces. By leveraging the ResNet50 architecture, the project will build a model capable of detecting various types of defects and distinguishing between different classes of anomalies. The system will be integrated with a database that stores labeled images of steel defects, facilitating training, testing, and validation of the model. Additionally, a user-friendly interface will be developed using Streamlit, allowing operators to upload images and receive real-time defect predictions.

The importance of this project lies in its potential to improve the overall quality control process in steel manufacturing, reducing the reliance on human inspectors, increasing accuracy, and providing real-time feedback. This not only addresses the limitations of manual inspection but also aligns with the goals of Industry 4.0 by integrating advanced technologies into the production process. Additionally, the initiative will add to the expanding corpus of research on deep learning and computer vision applications in industrial settings, offering insightful information for upcoming advancements in automated quality control systems.

1.2 Statement of the Problem

Manual inspection of steel surfaces for defects is not only time-consuming but also prone to human error. Given the high demand for steel and the strict quality requirements in various industries, relying solely on manual inspection methods is inefficient and often leads to inconsistent results. Moreover, human inspectors may miss small defects or misclassify them, leading to defective products being shipped to customers or, conversely, good products being flagged unnecessarily.

The problem at hand is how to design an automated system that can accurately detect and classify defects on steel surfaces in real-time, thereby reducing human error and increasing the efficiency of the inspection process. This system should be scalable, adaptable to different kinds of surface defects, and capable of providing real-time feedback for industrial applications. The study aims to tackle this challenge by developing a deep learning-based model using ResNet50, combined with a user-friendly interface through Streamlit, to ensure ease of use and integration within existing industrial workflows.

1.3 Aim and Objectives of the Project Work

The primary aim of this project is to design and implement an automated system that uses deep learning techniques for detecting and classifying surface defects on steel. This will improve the accuracy, speed, and consistency of defect detection in the manufacturing process.

The objectives are:

1. To design a database schema that organizes and stores images of steel defects for model training and validation.
2. To use the ResNet50 architecture to develop a deep learning model that can accurately detect and classify steel surface defects.
3. To build a user-friendly interface using Streamlit for real-time image uploads and defect classification.
4. To evaluate the model's performance using accuracy metrics and adjust the model based on testing results.
5. To assess the system's potential for integration into industrial production lines and its impact on quality control.

1.4 Significance of Project Work

The significance of this project lies in its ability to address the challenges faced by the steel industry in maintaining high standards of quality control. By automating the defect detection process, the system reduces the reliance on manual inspection, improves the accuracy and speed of defect classification, and ensures consistency across large volumes of steel production. This contributes to significant cost savings, as defects can be identified early in the production process, preventing the shipment of faulty products and reducing material waste.

Moreover, the project has broader implications for the future of industrial quality control. The techniques and methodologies developed for steel defect detection can be adapted and applied to other industries, such as automotive and electronics manufacturing, where surface defects play a critical role in product quality. This project also contributes to the advancement of computer vision and deep learning research, specifically in the context of industrial automation.

1.5 Scope of the Project Work

This project focuses on the detection and classification of surface defects on steel plates. The core areas include:

- Designing a database schema to store and manage labeled images of steel defects.
- Building and training a ResNet50-based deep learning model to classify different types of steel surface defects.
- Developing a Streamlit-based interface to enable users to upload steel images and receive real-time classification results.
- Evaluating the model's performance using various accuracy metrics and refining the model for optimal results.
- Integrating the system into a workflow suitable for real-time industrial applications.

1.6 Limitations of the Project Work

Some limitations of the project include:

- The model is trained specifically on steel defects and may not generalize well to other materials without further training.
- The model's performance is influenced by the quality and diversity of the training dataset. The model's capacity to generalise to novel, unobserved fault types may be impacted by a small dataset.
- Real-time deployment in a manufacturing setting requires additional hardware considerations, which are outside the scope of this project.
- The system focuses only on surface defects and does not address subsurface defects, which may require different detection techniques.

1.7 Organisation of the Study

This study is organized as follows:

- Chapter One introduces the background, problem statement, objectives, significance, scope, and limitations of the study.
- Chapter Two provides a literature review on the detection and classification of steel defects, with a focus on computer vision and deep learning approaches.
- Chapter Three discusses the methodology, including the design of the database, the architecture of the deep learning model, and the tools used for development and testing.
- Chapter Four presents the results of the model evaluation, including accuracy, confusion matrices, and error analysis.
- Chapter Five concludes the study, summarizes the findings, and provides recommendations for future work.

1.8 Definition of Terms

- **Computer vision**: A field of artificial intelligence focused on enabling computers to interpret and understand visual information from the world.
- **Defect Classification**: The process of identifying and categorizing defects on a material's surface based on their characteristics, such as size, type, and location.
- **Deep Learning**: A branch of machine learning that learns data representations and generates predictions using multi-layered neural networks.
- **ResNet50**: A deep convolutional neural network architecture that enhances picture classification tasks using residual learning.
- **Streamlit**: An open-source framework for building interactive web applications, often used to create dashboards and visualizations for machine learning models.
- **Convolutional Neural Network (CNN):** A kind of deep learning model made to handle data with a grid-like structure, like pictures.
- **Data Augmentation**: A technique used in machine learning to increase the diversity of the training dataset by applying random transformations, such as rotations and flips, to input data.
- **Model fine-tuning**: The process of unfreezing and retraining a portion of the model layers after initial training to improve performance.

CHAPTER TWO: LITERATURE REVIEW

2.1 Automated Defect Detection in the Steel Industry

The steel manufacturing industry, like many other industrial sectors, faces significant challenges in maintaining product quality due to various surface defects that occur during production processes. Surface defects, such as cracks, scratches, pitting, and inclusions, not only affect the aesthetics but also compromise the structural integrity of the final steel products. Traditionally, the detection of these defects has been predominantly performed through manual inspection, a process that is labor-intensive, time-consuming, and highly prone to human error (Zhou et al, 2021). Manual inspections are limited by the inspectors' expertise and fatigue, which can lead to inconsistent and subjective evaluations, resulting in suboptimal quality control. This situation presents a critical need for more efficient, reliable, and scalable methods to enhance defect detection in steel production.

The emergence of machine learning (ML) and artificial intelligence (AI) technologies in recent years, especially in computer vision, has offered encouraging options for automating fault identification procedures. Defect detection and classification automated technologies are quickly becoming competitive alternatives to manual inspection. According to Jiang et al. (2019), these systems have the ability to increase the speed and accuracy of defect identification, which can result in improved quality control, lower costs, and less production line downtime.

Convolutional neural networks (CNNs) and other DEEP LEARNING techniques are at the core of these automated systems. CNNs' capacity to automatically extract and learn hierarchical features from unprocessed visual input has made them the industry standard for image analysis tasks. The architecture of CNNs, which mimics the visual processing in the human brain, allows them to capture spatial hierarchies in images, making them ideal for recognizing complex patterns and subtle differences that may indicate a defect (LeCun et al., 2015). CNNs are particularly adept at identifying steel defects, as they can handle large volumes of data and adapt to various defect types, which would otherwise be challenging for traditional computer vision algorithms or manual inspections.

The benefits of using deep learning-based systems for defect detection in the steel industry are multifaceted. First, these systems offer SCALABILITY—once trained, they can process a large number of images in real time, significantly outpacing the inspection capacity of human workers. This is especially beneficial in high-volume production environments where manual inspection would be impractical. Additionally, automated systems provide CONSISTENCY in defect detection, eliminating the subjectivity associated with human inspectors. The models can continuously learn from new data, improving their accuracy over time and adapting to changes in production processes or defect types (Zhu et al., 2020).

Another important advantage of automated defect detection systems is their ability to operate in harsh industrial environments where human inspectors may face limitations due to safety concerns, lighting conditions, or other environmental factors. For instance, some defects may be difficult to detect under poor lighting, or they may be located in hard-to-reach areas of a steel sheet, which could be challenging for manual inspection (Lin et al., 2019). With automated systems, these challenges are mitigated, as the machines can be configured to perform inspections under various conditions, using advanced imaging techniques like infrared or X-ray imaging to capture defects invisible to the naked eye (Zhang et al., 2020).

Furthermore, by integrating automated defect detection systems with REAL-TIME FEEDBACK mechanisms, manufacturers can implement predictive maintenance and immediate corrective actions. This helps in preventing defective products from advancing further in the production pipeline, thereby reducing waste and improving operational efficiency. This integration is critical in industries like steel manufacturing, where defect detection must be performed continuously and with minimal downtime (Khan et al., 2021). The real-time nature of these systems also enables manufacturers to gather valuable data on defect occurrence patterns, which can be used for process optimization and long-term improvement of product quality.

Despite the significant advancements in automated defect detection, challenges remain. Training deep learning models requires large, annotated datasets that represent all possible defect types and variations. Obtaining such datasets can be difficult in the steel industry, where certain defects may be rare, and labeling the data accurately requires domain expertise (Sun et al, 2018). Additionally, while CNNs are highly effective at feature extraction, their performance can degrade in the presence of NOISE or variations in image quality, such as reflections or inconsistent lighting, which are common in industrial settings. Researchers are actively exploring ways to improve the robustness of these models, such as through DATA AUGMENTATION and the use of more advanced network architectures like GENERATIVE ADVERSARIAL NETWORKS (GANS)to simulate defect variations for training purposes (Goodfellow et al., 2014).

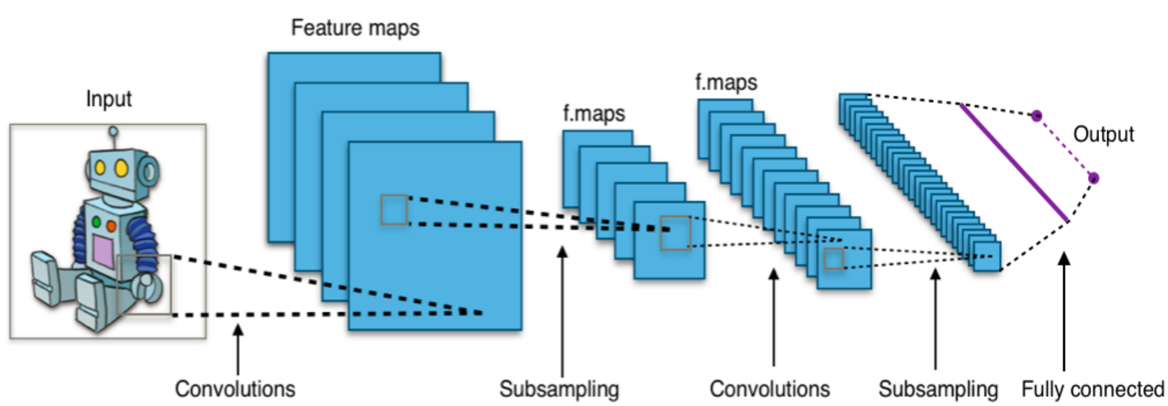
Automated defect detection systems powered by deep learning are transforming the steel industry by offering a faster, more reliable, and scalable alternative to traditional inspection methods. These systems are not only improving the accuracy of defect detection but also enabling manufacturers to implement smarter production processes that minimize defects and optimize overall product quality. As these technologies continue to evolve, the steel industry stands to benefit from ongoing advancements in machine learning, imaging techniques, and real-time data processing, paving the way for more intelligent and automated production lines.

2.2 Deep Learning and Convolutional Neural Networks

Recent years have seen tremendous progress in deep learning, a branch of machine learning, especially with the creation of CNNs. CNNs are perfect for image analysis applications because they can automatically learn the spatial hierarchies of features from input photos (Simonyan & Zisserman, 2014). CNNs are especially effective for jobs like flaw detection in photographs of steel surfaces because they learn directly from raw pixel data, unlike typical machine learning techniques that rely on manually created features.

Figure 1 shows the basic architecture of a CNN, which is made up of convolutional, pooling, and fully connected layers. Each convolutional layer applies a set of filters to the input image to detect various features, including corners, edges, and textures, while the pooling layers down-sample the feature maps, reducing their size and computational cost. The fully connected layers at the top of the network combine the learnt information to get the final classification (Simonyan & Zisserman, 2014).

Figure 1: Basic CNN Architecture



Source: Simonyan & Zisserman (2014)

Convolutional, pooling, and fully linked layers are commonly seen in CNN architectures. While pooling layers minimise the spatial dimensions while preserving the most important information, convolutional layers are in charge of extracting local features like edges, textures, and patterns. At the end of the network, the learnt attributes are aggregated in fully connected layers to make the final classification decision (He et al., 2016). CNNs can recognise both low-level features (like surface textures) and high-level features (like defect shapes) thanks to their hierarchical approach, which makes them extremely effective at defect detection tasks.

2.2.1 Transfer Learning in Defect Detection

The creation of transfer learning strategies has been one of the main advances in deep learning. Without starting from scratch, transfer learning enables pre-trained models—like ResNet, VGG, and MobileNet—to be optimised for certain applications (Pan & Yang, 2010). This is especially helpful in defect identification, where it can be difficult to find sizable, labelled datasets for deep network training. A significant amount of labelled data is needed for classical machine learning since models are created from the ground up for every new task. However, transfer learning drastically cuts down on training time and data needs by applying knowledge learnt from addressing one problem to other, related problems (Weiss, Khoshgoftaar, & Wang, 2016).

In the context of steel defect detection, transfer learning has been widely adopted. Pre-trained CNNs, such as ResNet50, VGG16, and InceptionV3, are initially trained on large-scale datasets like IMAGENET, which contains millions of labeled images across thousands of classes. These models learn generalized image features, such as edges, textures, and shapes, that can be transferred to other image classification tasks. For steel defect detection, the pre-trained models are fine-tuned on smaller datasets that contain images specific to steel defects, such as cracks, pitting, and inclusions, allowing them to leverage the features learned from generic images and apply them to defect detection tasks (He et al., 2016). This approach significantly reduces the computational resources and time required to train the model while maintaining high accuracy in detecting defects (Zhang et al, 2020).

Transfer learning is especially useful in fields where obtaining labelled data is difficult, costly, or time-consuming. Taking pictures of defects and correctly labelling them is a time-consuming procedure that calls for subject knowledge in the steel industry. Therefore, the significant costs and time constraints associated with gathering huge datasets can make it unfeasible to train deep learning models from scratch (Oquab et al, 2014). Transfer learning is a useful technique for automating defect identification procedures in production environments because it gets over this problem by enabling models to attain high accuracy with a comparatively limited number of labelled defect photos (Razavian et al, 2014).

The capacity of the pre-trained models to generalise effectively across various fault kinds, even when only a limited number of instances are given, is a noteworthy benefit of employing transfer learning in defect detection. This is due to the fact that the model's initial training on extensive datasets such as ImageNet aids in the collection of general visual patterns that may be applied to a variety of applications. After learning these patterns, the model simply needs a little amount of extra training to adjust its parameters for the particular defect detection job (Shin et al., 2016). This generalisability is especially useful in the steel industry, where production processes and environmental factors can significantly alter the types and appearances of defects (Wang et al., 2017).

Another key benefit of transfer learning is the computational efficiency it offers. Training deep learning models, such as ResNet or VGG, from scratch typically requires substantial computational power and time. However, transfer learning enables the use of pre-trained weights from models that have already undergone extensive training, reducing the need for large-scale computations. This efficiency is particularly important in industrial settings where real-time or near-real-time defect detection is required to minimize downtime and ensure continuous production (Zhao et al., 2021).

Moreover, transfer learning allows for DOMAIN ADAPTATION, which is critical in defect detection where the visual characteristics of defects can vary significantly between different manufacturing processes or materials. Fine-tuning pre-trained models enables the adaptation of these models to specific domains without the need for extensive retraining (Hussain et al., 2018). In steel manufacturing, defects may differ in appearance based on factors like the type of steel, the stage of the manufacturing process, or the environment in which the steel is produced. Transfer learning enables models to adapt to these variations by learning domain-specific features during fine-tuning (Csurka, 2017).

The success of transfer learning in defect detection is evidenced by numerous studies that have applied this technique across various industries. For example, Chen et al. (2020) used transfer learning to detect defects in electronic components, demonstrating that models pre-trained on ImageNet could be effectively fine-tuned to detect defects with limited data. Similarly, Zhang et al. (2020) applied transfer learning to detect surface defects in steel sheets and achieved a significant improvement in classification accuracy compared to models trained from scratch. These examples highlight the versatility and effectiveness of transfer learning in addressing the challenges of defect detection across different industrial applications.

While transfer learning has shown great promise, it is not without challenges. One issue is the potential for OVERFITTINGduring fine-tuning, particularly when the target dataset is small or lacks sufficient variability. Overfitting occurs when the model becomes too specialized in the training data, resulting in poor generalization to new, unseen examples. To mitigate this risk, techniques such as DATA AUGMENTATION and REGULARIZATION are often employed to artificially increase the size and diversity of the training set, making the model more robust (Shorten & Khoshgoftaar, 2019). Additionally, the choice of which layers to fine-tune can impact the performance of the transfer learning model. Researchers have found that freezing the earlier layers of the network, which capture more general features, while fine-tuning the later layers, which capture more task-specific features, is often the most effective strategy (Yosinski et al., 2014).

Transfer learning has become a cornerstone of automated defect detection in industrial applications, particularly in the steel industry. By leveraging pre-trained models, manufacturers can develop robust defect detection systems with limited data, reducing the need for extensive manual labeling and enabling faster deployment of AI-based quality control systems. As transfer learning techniques continue to evolve, they are likely to play an increasingly important role in driving innovation in defect detection and other industrial automation tasks.

2.2.1.1 ResNet50 for Steel Surface Defect Detection

ResNet50, a 50-layer deep convolutional neural network (CNN), is widely recognized for its high performance in image classification tasks, including defect detection in industrial settings. One of its main contributions to deep learning is the introduction of residual connections, which allow the network to bypass certain layers, effectively mitigating the vanishing gradient problem that traditionally hampers the training of deep networks (He et al, 2016). These residual connections enable ResNet50 to propagate information across the network more effectively, allowing it to learn complex features at various levels of abstraction. This capability makes ResNet50 particularly well-suited for tasks that require detailed visual analysis, such as identifying small, subtle, or overlapping defects on steel surfaces.

In the domain of defect detection, ResNet50 has demonstrated strong capabilities in both academic research and industrial applications. For instance, **Liu et al. (2019)** applied ResNet50 for defect classification on a dataset of steel surface images. Their study faced challenges such as class imbalance and limited data, which constrained the model's overall accuracy to 75%. This outcome highlights the importance of addressing issues such as data imbalance through techniques like data augmentation to improve classification results. This also emphasizes the critical role of properly curated datasets in achieving optimal performance in defect detection tasks.

Moreover, ResNet50 has been shown to outperform other traditional machine learning and shallow CNN models due to its deep architecture and efficient use of computational resources. While older models such as VGG16 and AlexNet require extensive computational power and often suffer from overfitting or underfitting when trained on small datasets, ResNet50's use of residual learning enables it to train effectively even on relatively smaller datasets without sacrificing performance (Wang et al, 2019). This is particularly important in the context of steel manufacturing, where collecting large-scale labeled datasets of defects can be both time-consuming and expensive. With ResNet50, the need for massive amounts of training data is alleviated, allowing it to perform well in real-world defect detection scenarios where data availability may be limited (Khan et al, 2019).

The flexibility of ResNet50 also makes it highly adaptable for transfer learning, a process in which a pre-trained model is fine-tuned on a specific dataset. In many steel surface defect detection tasks, ResNet50 models are first pre-trained on large datasets like ImageNet, which includes millions of labeled images of everyday objects, and then fine-tuned on smaller, domain-specific datasets containing images of steel defects (Zhang et al., 2020). This transfer learning approach enables the model to leverage the general image features it has learned from ImageNet while adapting to the unique characteristics of steel surface defects with minimal additional training. Transfer learning using ResNet50 has been found to significantly reduce the time and computational power required to train a model, while still achieving high levels of accuracy and precision (Huang et al, 2021).

Further studies have explored the integration of ResNet50 with additional techniques such as data augmentation and ensemble learning to improve its performance in defect detection tasks. For example, in a recent study by Zhao et al. (2021), data augmentation techniques such as random rotations, flips, and zooms were applied to the training images to artificially expand the dataset, reducing overfitting and improving the model's ability to generalize to unseen defect types. In combination with ensemble learning, where multiple ResNet50 models are trained on different subsets of the data and their predictions are aggregated, the researchers were able to achieve even higher classification accuracies, highlighting the robustness of ResNet50 when applied in complex industrial environments.

In addition to its performance in classification, ResNet50 has also been utilized in real-time defect detection systems, where the speed and accuracy of the model are critical. In high-volume steel production lines, defects need to be identified and rectified as quickly as possible to avoid costly production delays and ensure product quality. The relatively lightweight architecture of ResNet50, compared to deeper models like ResNet101 or ResNet152, makes it an ideal choice for real-time applications, where computational efficiency is paramount (Ren et al., 2020). By deploying ResNet50 models on edge devices or within cloud-based systems, manufacturers can achieve real-time defect detection and classification, enhancing quality control processes and reducing manual inspection efforts (Chen et al, 2021).

Despite its advantages, it is important to note that ResNet50 may still face challenges when dealing with highly imbalanced datasets, a common issue in defect detection tasks where some defect types are much rarer than others. In such cases, techniques like class weighting, data augmentation, and synthetic oversampling are often employed to mitigate the effects of class imbalance and ensure that the model does not become biased toward more frequent defect types (Sun et al, 2019). Furthermore, by employing methods like Grad-CAM (Gradient-weighted Class Activation Mapping), which visualises the areas of the image that the model concentrates on during prediction, researchers are continuing to investigate methods to improve the interpretability of ResNet50 models in defect detection tasks (Selvaraju et al., 2017).

In conclusion, ResNet50's deep design, residual connections, and transfer learning adaptability have made it a successful tool for detecting steel surface defects. It is a useful tool for automated defect detection systems in the steel industry because of its capacity to generalise across many defect types, even with little data. ResNet50 is probably going to continue to be a crucial part of contemporary quality control systems in manufacturing settings as long as research into its use in defect identification is conducted.

2.2.1.1.1 Data Augmentation and Class Imbalance

One of the most persistent challenges in training convolutional neural networks (CNNs) for defect detection tasks, particularly in industrial settings, is the imbalance in datasets. In real-world scenarios, certain types of defects—such as scratches or surface pits—may occur far more frequently than others, leading to an imbalanced dataset where the model becomes biased toward the more frequent classes (Buda et al., 2018). This imbalance poses a significant risk in production environments, as the model may fail to identify rare but critical defects, jeopardizing the overall quality of the product.

To mitigate this issue, data augmentation has become a crucial strategy in machine learning workflows for defect detection. Data augmentation techniques, including image rotation, scaling, flipping, and translation, artificially enhance the diversity of the training set by generating new variations of existing images. These transformations allow the model to learn from a more varied dataset, making it more robust to unseen data and improving its generalization capabilities (Shorten & Khoshgoftaar, 2019). For example, in steel defect detection, augmented images that simulate various angles and lighting conditions can help the model become more adept at identifying defects that may not be perfectly aligned with the camera during actual inspections (Perez & Wang, 2017).

Researchers have extensively demonstrated the positive impact of data augmentation in addressing class imbalance. In a study conducted by Wong et al. (2016), data augmentation was applied to a defect detection dataset with highly imbalanced classes, where rare defects comprised less than 5% of the total dataset. The researchers found that augmentation techniques significantly improved the model's ability to detect these rare defect types, increasing both precision and recall. The combination of transformations such as flipping, cropping, and brightness adjustment contributed to enhanced model performance by preventing overfitting to dominant classes while exposing the model to more diverse examples.

Beyond traditional augmentation methods, more advanced approaches like synthetic oversampling techniques have also been explored to handle class imbalance in defect detection. One popular method is the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic samples of the minority class by interpolating between existing samples (Chawla et al., 2002).

SMOTE has been effectively integrated with CNNs to combat the severe class imbalance commonly encountered in industrial applications, including steel surface defect detection (Han et al., 2020). By generating additional samples for underrepresented defect types, SMOTE enables the model to better capture the unique features of rare defects, leading to improved classification performance.

Another widely adopted approach to address class imbalance is through class weighting. In this technique, the loss function of the CNN is modified such that misclassifications of the minority class are penalized more heavily than those of the majority class (Huang et al., 2016). This weighting mechanism forces the model to place greater emphasis on accurately predicting the less frequent classes, which are often more critical in defect detection tasks. For instance, in the context of steel defect classification, misclassifying a rare but significant defect such as an inclusion or pitted surface could have serious consequences on the final product's integrity (Chen et al., 2021). By assigning higher penalties to these misclassifications, class weighting ensures that the model remains attentive to all defect types, regardless of their frequency in the training data.

Despite these advancements, balancing the trade-offs between class weighting, data augmentation, and other strategies remains a challenge. While data augmentation increases the variety of training samples and improves generalization, excessive augmentation can sometimes introduce noise, leading to degraded model performance (Zhong et al., 2020). Similarly, class weighting can improve performance on minority classes but may also lead to overfitting if not applied carefully. Researchers continue to explore hybrid approaches that combine multiple techniques to optimize model performance. For example, in a recent study, He et al. (2020) combined data augmentation, class weighting, and ensemble learning to develop a robust defect detection model. This approach enabled the model to achieve higher accuracy across all defect classes, demonstrating the potential of integrated methods in industrial applications.

Moreover, emerging techniques such as Generative Adversarial Networks (GANs) have shown promise in addressing class imbalance by generating realistic synthetic images of rare defect types (Goodfellow et al., 2014). GANs consist of two neural networks—a generator and a discriminator—that compete with each other to produce realistic synthetic data. In the context of defect detection, GANs can generate synthetic images of rare defects that are virtually indistinguishable from real images, thereby enhancing the representation of minority classes in the dataset (Wang et al., 2021). Studies have shown that using GAN-generated images alongside traditional data augmentation can lead to significant improvements in classification performance, particularly for underrepresented defect categories (Zhu et al., 2020).

Combining data augmentation, class weighting, and synthetic oversampling approaches is necessary to overcome the difficulties caused by class imbalance in defect detection tasks. More sophisticated techniques like SMOTE and GANs provide extra benefits in managing uncommon fault kinds, even though conventional augmentation techniques like rotation, flipping, and scaling are still useful. It is anticipated that hybrid approaches that combine these approaches would improve the precision and resilience of CNN-based defect detection systems in industrial settings as this field of study develops.

2.3 Real-Time Defect Detection Systems

Real-time defect detection plays a pivotal role in manufacturing processes where the immediate identification of defects is crucial for ensuring product quality and minimizing production waste. In industries like steel production, surface defects such as scratches, cracks, and pitting can degrade the material's integrity and aesthetic quality, resulting in significant financial losses due to rejected batches and machine downtime (Zhou et al., 2021). The integration of real-time defect detection systems into production lines allows for continuous monitoring of steel surfaces, identifying anomalies as they occur and enabling swift corrective action, thus improving overall production efficiency.

These systems typically incorporate three key components: (1) a high-resolution camera that captures real-time images of the steel surface as it passes through the production line, (2) a convolutional neural network (CNN) that processes the captured images to detect defects, and (3) a feedback mechanism that either alerts the operator or halts production when defects are identified (Kang et al., 2019). In this way, real-time defect detection systems contribute to reducing the incidence of defective products and mitigating the risks associated with delayed defect identification, which could otherwise lead to extensive material wastage and costly rework.

One of the primary advantages of real-time defect detection systems is their ability to perform non-invasive, high-speed inspections in industrial settings. In traditional inspection methods, human operators are often tasked with visually identifying defects, which is time-consuming, prone to errors, and unsuitable for high-volume production environments (Voulodimos et al., 2018). Automated systems, on the other hand, can process thousands of images per second, providing near-instantaneous feedback on the quality of the product. This immediate feedback loop enables manufacturers to detect problems early in the production process and take corrective action, such as adjusting machine parameters or halting production, before the defects escalate into larger issues (LeCun et al., 2015).

In recent years, the development of lightweight deep learning models such as MobileNetV2 has further enhanced the feasibility of real-time defect detection in resource-constrained environments.

MobileNetV2, in particular, leverages depthwise separable convolutions, which significantly reduce computational complexity compared to traditional CNNs while maintaining high levels of accuracy (Sandler et al., 2018). This makes it an ideal choice for deployment in industrial settings where computational resources may be limited, such as on embedded devices or edge computing platforms. By reducing the computational load, MobileNetV2 allows real-time defect detection systems to operate efficiently without sacrificing performance, thus enabling faster and more scalable deployment in production environments (Howard et al., 2019).

The use of advanced imaging technologies has also contributed to the effectiveness of real-time defect detection systems. High-speed cameras equipped with advanced lighting systems can capture images of steel surfaces with high levels of detail, even at fast production speeds (Xu et al., 2020). These images are then fed into the CNN for processing, allowing the model to detect even subtle defects that may be difficult to spot with the naked eye. By combining high-quality imaging with powerful deep learning models, manufacturers can achieve unprecedented levels of accuracy and reliability in defect detection, reducing the risk of faulty products reaching the market (Zhang et al., 2020).

Real-time defect detection systems also integrate feedback mechanisms that allow for automatic responses to detected defects. For instance, in steel production, if a surface defect is detected, the system can automatically halt the production line, preventing further processing of defective material. This capability is particularly important in high-stakes industries where undetected defects can lead to significant financial and safety risks. In some cases, defect detection systems are connected to machine learning algorithms that can automatically adjust machine parameters to correct the defect, further improving the efficiency and reliability of the production process (Bermudez et al., 2021).

Moreover, real-time defect detection is not limited to traditional manufacturing environments. With the rise of Industry 4.0 and smart factories, these systems are becoming increasingly integrated into fully automated production lines that rely on artificial intelligence and machine learning to optimize operations. In such environments, defect detection systems work alongside other intelligent systems to monitor production quality, predict maintenance needs, and optimize production schedules, all in real-time (Lee et al., 2017). As a result, manufacturers can achieve higher levels of productivity, reduce waste, and ensure consistent product quality, all while minimizing human intervention.

While real-time defect detection systems offer numerous benefits, there are also challenges that must be addressed for widespread adoption. One of the main challenges is ensuring the robustness of the system in different production environments. For example, variations in lighting conditions, surface textures, and production speeds can affect the accuracy of defect detection. To mitigate these challenges, researchers are developing more robust CNN models that can adapt to varying environmental conditions and maintain high detection accuracy in diverse industrial settings (Zhang et al., 2020). Additionally, real-time systems must balance the need for speed and accuracy. High-speed production environments require systems that can process images quickly without sacrificing detection performance, which is why lightweight models like MobileNetV2 are increasingly favored for such applications (Howard et al., 2019).

Real-time defect detection systems have become essential in modern manufacturing processes, especially in industries like steel production where surface defects can lead to costly material waste and downtime. The integration of high-speed cameras, advanced CNN models, and feedback mechanisms allows for continuous monitoring and rapid response to defects, improving overall production efficiency and product quality. As lightweight models like MobileNetV2 continue to evolve, these systems will become even more accessible and efficient, further transforming industrial quality control practices.

2.3.1 Streamlit and User Interface Integration

Incorporating user-friendly interfaces into automated defect detection systems is essential for ensuring that operators, quality control personnel, and other non-technical users can efficiently interact with and leverage the system's capabilities. The success of such systems often depends not only on their accuracy and speed but also on their accessibility and ease of use in a real-world environment. Streamlit, an open-source Python framework, provides an effective solution for integrating deep learning models into interactive, web-based interfaces with minimal coding effort. This framework allows developers to create intuitive and responsive web applications that present model outputs in real time, making it an ideal choice for industrial applications like defect detection in steel manufacturing (Chollet, 2018).

The integration of Streamlit in defect detection systems for the steel industry enables operators to upload images of steel surfaces and receive instant feedback on potential defects, enhancing the overall decision-making process. This capability is particularly valuable in high-throughput production environments, where timely and accurate defect classification can help prevent defective products from moving further down the production line, thereby minimizing waste and reducing production costs (Zhou et al., 2021). By providing a user-friendly interface that displays defect classification results, confidence scores, and detailed probabilities for each defect class, Streamlit makes the advanced capabilities of deep learning models accessible to users without requiring them to understand the underlying technology (Zhu et al., 2020).

One of the key benefits of Streamlit is its simplicity in transforming complex machine learning workflows into interactive applications. Streamlit automatically updates the user interface in response to changes in the code, eliminating the need for manual front-end development typically required when building web applications (Sarma et al., 2020). For instance, in a defect detection system, the user can simply upload a batch of steel surface images, and the Streamlit application processes the images using a deep learning model, such as ResNet50 or MobileNetV2, to classify the defects. The results are immediately displayed on the interface, complete with visual indicators, such as color-coded heatmaps or confidence bars, that help users easily interpret the predictions (Howard et al., 2019).

Moreover, Streamlit supports the integration of various data visualization libraries, such as Matplotlib and Seaborn, enabling developers to create more sophisticated visual outputs, including confusion matrices and performance charts (McKinney, 2017). These visualizations provide operators with deeper insights into the model's performance, highlighting areas where the model might struggle to differentiate between certain defect types. For example, a confusion matrix can reveal how often the model confuses "Pitted Surface" defects with "Rolled-in Scale" defects, prompting further investigation into the root causes of these misclassifications and possible improvements to the model or dataset (Sandler et al., 2018). Such detailed feedback can be instrumental in continuously refining the model's accuracy and robustness, especially in environments with high variability in defect types and production conditions.

Streamlit also supports real-time data input and feedback, which is crucial for real-time defect detection in industrial settings (Shen et al., 2019). In a steel manufacturing plant, the system can be connected to high-speed cameras that continuously capture images of steel surfaces as they pass through the production line. These images can then be fed into the deep learning model, and the predictions can be displayed on a Streamlit dashboard in real time. Operators can use this feedback to make immediate decisions, such as halting the production line if a severe defect is detected, thereby preventing further damage to the product or the equipment (Kang et al., 2019).

Another advantage of Streamlit is its ability to run on low-resource systems, making it suitable for deployment in industrial environments where computational resources might be limited (Wong et al., 2016). While traditional defect detection systems often require powerful servers or cloud-based platforms to handle large volumes of data and complex computations, Streamlit allows for the deployment of lightweight applications that can operate on local machines or edge devices. This capability is particularly beneficial in industries like steel manufacturing, where real-time defect detection systems must operate continuously with minimal latency and downtime (LeCun et al., 2015).

Furthermore, Streamlit's integration with Python-based deep learning frameworks, such as TensorFlow and Keras, allows developers to seamlessly incorporate pre-trained models, fine-tune them for specific defect detection tasks, and deploy them in production environments with minimal effort (He et al., 2016). For instance, a pre-trained ResNet50 model can be fine-tuned on a dataset of steel surface defects and deployed using Streamlit, providing a real-time interface for defect detection that operators can use directly on the shop floor. The interface can also be customized to include additional features, such as defect severity ratings or historical performance metrics, giving operators a comprehensive tool for monitoring and improving the quality of steel products (Liu et al., 2020).

In summary, the integration of Streamlit into defect detection systems represents a significant advancement in making deep learning technologies more accessible and practical for industrial applications. By providing a user-friendly interface that enables real-time interaction with advanced machine learning models, Streamlit enhances the usability and effectiveness of defect detection systems in steel manufacturing. This ease of use, combined with the framework's ability to handle real-time data and integrate with powerful visualization tools, makes it a valuable tool for improving quality control and reducing waste in production processes.

2.4 Challenges in Automated Defect Detection

Despite significant advancements in automated defect detection technologies, several challenges continue to hinder their full adoption in industrial settings. One of the primary challenges is the high variability in steel surface textures, lighting conditions, and environmental factors that can impact the accuracy of defect detection systems. Variations in lighting conditions, for example, can cause inconsistent reflections or shadows on the steel surfaces, which may lead to both false positives and false negatives (Zhou et al., 2021). Inconsistent lighting can make certain defects more challenging to detect, especially minor surface defects like scratches or small inclusions. This problem is exacerbated in high-speed production lines where lighting cannot be fully controlled, and the steel surface is constantly moving (Kang et al., 2019).

To address these issues, researchers are increasingly focusing on developing more sophisticated data augmentation techniques. Data augmentation simulates a broader range of environmental conditions during the training phase by applying transformations like rotation, brightness adjustments, and random cropping to the training images (Shorten & Khoshgoftaar, 2019). By training the model on artificially augmented images that mimic various real-world lighting conditions, reflections, and surface textures, deep learning models can become more robust and generalizable. For instance, data augmentation can help the model learn how to detect defects even in poor lighting conditions, thereby improving its performance in less-than-ideal environments (Wong et al., 2016).

Another persistent challenge in automated defect detection systems is the generalization ability of deep learning models. While pre-trained models such as ResNet50 have demonstrated excellent performance on well-defined datasets of specific defect types, their effectiveness tends to decline when applied to new datasets or different production environments (He et al., 2016). This issue arises because these models are often trained on data that reflects a narrow range of defect types and production conditions, limiting their ability to generalize to new or unseen scenarios. For instance, a model trained to detect surface defects on cold-rolled steel may struggle to accurately classify defects on hot-rolled steel, where the surface textures and defect characteristics differ significantly (Zhu et al., 2020).

To overcome this limitation, transfer learning and domain adaptation techniques are gaining traction in the field of defect detection. Transfer learning involves fine-tuning a pre-trained model on a smaller, domain-specific dataset, allowing the model to retain its general feature extraction capabilities while adapting to the nuances of the new dataset (Pan & Yang, 2010). Domain adaptation, on the other hand, focuses on reducing the domain shift between different datasets by aligning the feature distributions of the source and target domains (Ganin et al., 2016). These techniques enable deep learning models to be adapted for various production lines without requiring extensive retraining from scratch, thereby improving their scalability and versatility (Zhang et al., 2020).

A further complication in automated defect detection is the issue of class imbalance within the datasets. In many industrial applications, certain types of defects are far more common than others, leading to highly imbalanced datasets. This imbalance can bias the model towards predicting the more frequent defect types while underperforming on the rarer defect classes, resulting in poor overall performance (Buda et al., 2018). Addressing class imbalance requires a combination of techniques, including data augmentation, class weighting, and oversampling of the minority classes (Krawczyk, 2016). By using class weights or synthetic oversampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique), models can be better trained to handle rare defects without overfitting to the more frequent classes (Chawla et al., 2002).

Moreover, computational resource limitations pose another challenge, particularly in real-time defect detection systems. Steel production lines often require real-time feedback, which means that defect detection models must process images quickly and efficiently to keep pace with production. High computational costs, large memory requirements, and latency issues can make it difficult to deploy complex models like ResNet50 in resource-constrained environments (Howard et al., 2019). To address this challenge, lightweight models like MobileNetV2, which use depthwise separable convolutions to reduce computational complexity, have been explored for real-time defect detection. These models strike a balance between accuracy and efficiency, allowing them to be deployed in production environments with limited hardware resources (Sandler et al., 2018).

In addition, ensuring the explainability of deep learning models is critical in industrial settings. Operators and quality control managers often need to understand why a model has flagged a particular area as defective. However, deep learning models are typically viewed as "black boxes," providing little insight into the decision-making process (Doshi-Velez & Kim, 2017). To mitigate this, researchers are working on developing explainable AI (XAI) techniques that can provide visual explanations for model predictions, such as highlighting the areas of the image that were most influential in the model's decision (Samek et al., 2017). These techniques can improve trust in automated systems by providing users with interpretable and actionable information about the defect classification process.

Lastly, the challenge of system integration must be addressed. Automated defect detection systems are not stand-alone solutions; they must be integrated with existing manufacturing processes, databases, and quality control systems. Ensuring seamless integration between these components, while maintaining high throughput and real-time capabilities, remains a complex task (Shen et al., 2019). Solutions involving cloud-based platforms and edge computing are being explored to allow for more flexible and scalable deployments of defect detection systems in diverse industrial environments (Xu et al., 2018).

2.5 Future Directions

The future of defect detection in steel manufacturing lies in the continued development of more efficient, accurate, and adaptable deep learning models. One area of research that holds promise is the integration of transfer learning with self-supervised learning, where models can learn useful representations from unlabeled data before being fine-tuned on labeled datasets (He et al., 2021). This approach could reduce the need for large amounts of labeled training data, which is often a bottleneck in the development of defect detection systems.

Additionally, the use of edge computing and IoT devices in manufacturing environments presents new opportunities for real-time defect detection. By deploying lightweight deep learning models directly on IoT devices, manufacturers can achieve real-time monitoring without relying on centralized cloud-based systems, reducing latency and improving response times (Sandler et al., 2018).

CHAPTER THREE: METHODOLOGY

3.1 Research Design

The research design for this project is structured to facilitate the automatic detection and classification of defects in steel using deep learning techniques, database management and real-time prediction through a web interface. This project follows a systematic approach consisting of various phases: data collection, data preprocessing, model training, evaluation, and deployment. This end-to-end methodology enables the development of a robust system tailored to effectively address the challenges in defect detection.

3.1.1 Data Collection and Preparation

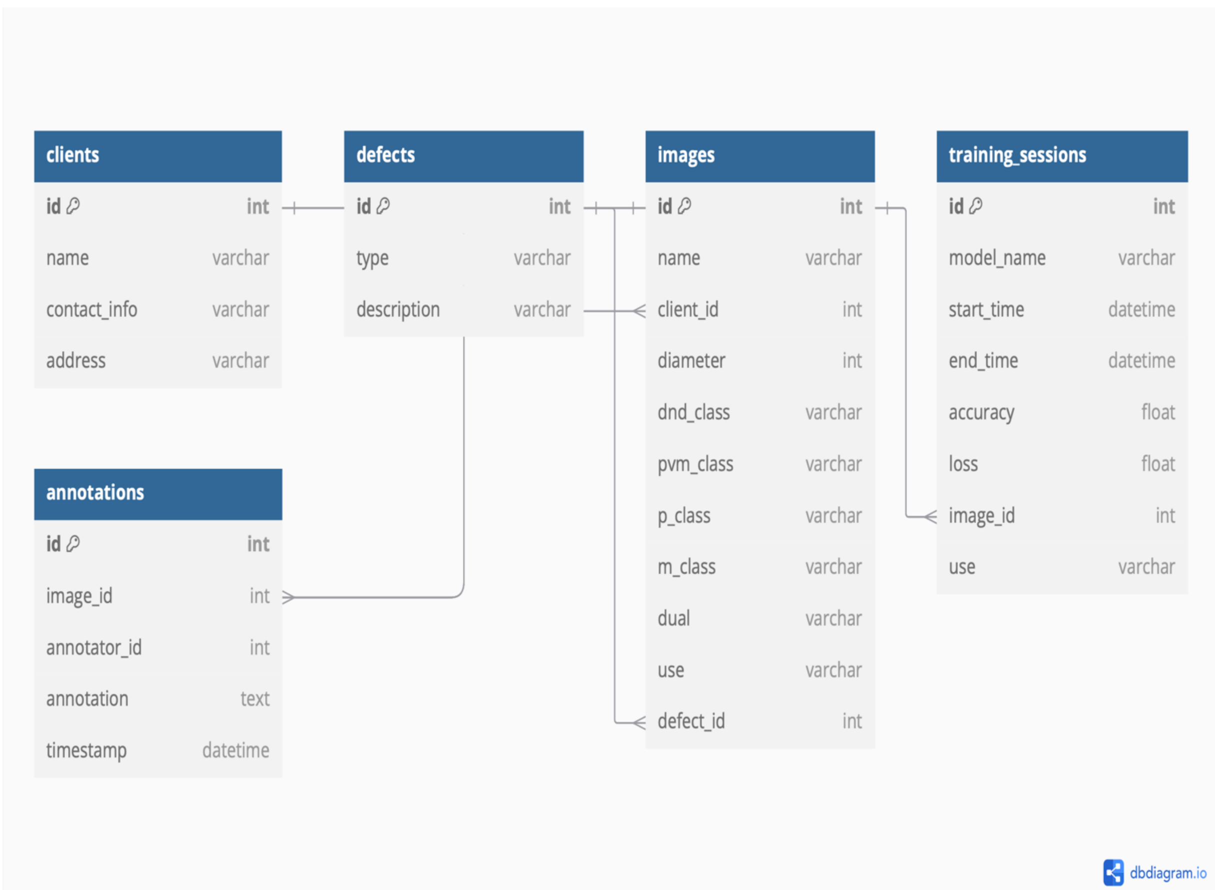
3.1.1.1 Dataset Description

The dataset utilized for this project comprises images of steel surfaces, which have been labeled based on various types of defects. The dataset is organized into different folders, each representing a unique defect category, including:

- CRAZING
- INCLUSION
- PATCHES
- PITTED SURFACE
- ROLLED-IN SCALE
- SCRATCHES

A total of 1440 images were collected, with 80% designated for training and 20% for validation purposes. The absence of a separate test set in this study means that the validation set serves a dual purpose: it is used for model evaluation during the training process. To manage the dataset effectively, an SQLITE database was used. The database schema includes tables to store image metadata such as file paths, defect labels, and whether the image is part of the training or validation set. This structure allows for efficient retrieval of data during the model training and evaluation process.

Figure 2: Below illustrates the basic schema of the database.



3.1.1.2 Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for model training. The following preprocessing techniques were employed:

- IMAGE RESIZING: In order to satisfy the input specifications of the ResNet50 architecture, all images were shrunk to 224x224 pixels.
- NORMALIZATION: Pixel values were normalized to a range between 0 and 1 by dividing the pixel intensity by 255, improving model convergence during training.
- DATA AUGMENTATION: To enhance the diversity of the training data and prevent overfitting, several data augmentation techniques were applied:
    - Random rotations (up to 40 degrees)
    - Width and height shifts (up to 40% of the total dimensions)
    - Zooming and shearing (up to 40%)
    - Horizontal flipping
    - Brightness adjustments (ranging from 0.7 to 1.3)
- CLASS WEIGHT CALCULATION: The "compute_class_weight" function from "sklearn.utils" was used to calculate class weights because to the possibility of class imbalance in the dataset. This ensures that less-represented classes receive appropriate attention during model training.

3.2 Model Development

The core of the defect detection system is built upon the RESNET50 architecture, a powerful convolutional neural network (CNN) known for its deep residual layers and strong performance in image classification tasks. To categorise steel surface defects, the ResNet50 model was refined after being pre-trained on IMAGENET.

3.2.1 Architecture Design

The ResNet50 architecture, which is renowned for its efficacy in image classification tasks, was used in the model creation process. The architecture was selected due to its robust performance in recognizing features and its ability to generalize well to new datasets.

Key modifications made to the original ResNet50 architecture include:

- GLOBAL AVERAGE POOLING LAYER: To reduce overfitting and create a compact representation of the feature maps.
- DENSE LAYERS: To reduce overfitting, two dense layers were introduced, a dropout layer after a 512-unit dense layer with a ReLU activation function.
- OUTPUT LAYER: To output the probability distribution across the six defect classes, a final dense layer with a softmax activation function was put into place.

3.2.2 Training Strategy

The training strategy involved two main phases:

1. INITIAL TRAINING: The initial phase froze the majority of the ResNet50 layers while training only the added dense layers. This approach allowed the model to leverage the pre-trained weights effectively while adapting to the specific characteristics of the steel defect dataset.
2. FINE-TUNING: After the initial training, the last 50 layers of the ResNet50 model were unfrozen for fine-tuning. This allowed the model to learn more intricate features associated with the specific defect classes present in the dataset.

The model was compiled using the Adam optimizer with a learning rate of `1e-5`, and the categorical cross-entropy loss function was used due to the multi-class classification nature of the problem. The model was trained for 30 epochs initially, followed by an additional 20 epochs during the fine-tuning phase.

3.3 Model Evaluation and Validation

3.3.1 Evaluation Metrics

The primary criteria used to assess the model's performance were accuracy and loss. Additionally, precision, recall, and F1-score were computed for every defect class to offer a more thorough assessment of the model. This comprehensive approach made sure that the model's advantages and disadvantages were fully understood.

3.3.2 Confusion Matrix and Performance Analysis

To illustrate the model's classification performance across all fault classes, a confusion matrix was created. The matrix highlighted true positives, false positives, and false negatives for every defect class, offering insights into the model's predictive capabilities.

3.4 System Deployment

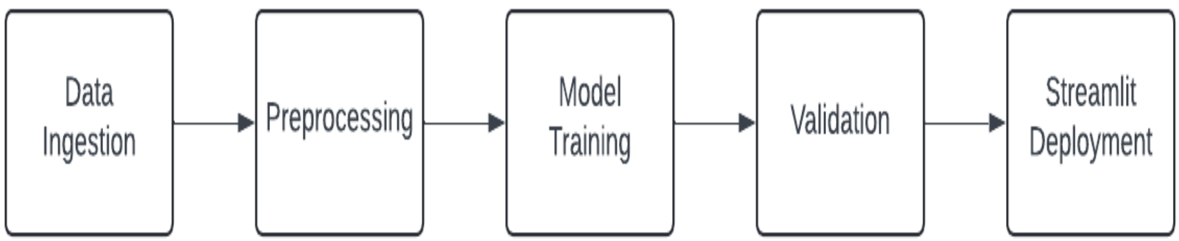
3.4.1 Deployment via Streamlit

Following the successful training and evaluation of the model, it was deployed using STREAMLIT, an open-source framework for building interactive web applications. The Streamlit application serves as a user-friendly interface, enabling users to upload images of steel surfaces and receive real-time defect classification predictions.

The application features:

- An image upload component, allowing users to submit images for classification.
- Real-time prediction outputs that display the predicted defect type and the associated confidence level.
- Class probabilities for all defect types, enabling users to understand the model's certainty in its predictions.

Figure 3: Below is an illustration of the end-to-end system;



3.5 Conclusion

This chapter outlined the systematic methodology employed in the project, detailing the processes involved in data collection, preparation, model development, evaluation, and deployment. By utilizing a structured approach and state-of-the-art techniques, the project aims to provide a robust solution for automating defect detection in steel manufacturing, addressing the industry's needs effectively.

CHAPTER FOUR: RESULTS DISCUSSION

4.1 Overview of the Results

This chapter discusses the results of the steel defect detection and classification model using ResNet50. The results focus on how the model performed during training and validation, as well as its evaluation using key performance metrics. The analysis includes the model's accuracy, loss, and confusion matrix. This chapter also highlights the challenges encountered during the process, such as data imbalance and overfitting.

This project's goal was to create a model that automatically divides steel surface flaws into six groups: inclusion, pitted surface, scratches, crazing, rolled-in scale, and patches. A bespoke dataset including photographs separated into training and validation sets was used to train the model. The findings in this chapter show the model's generalisation skills as well as the training procedure, assessed on unobserved data.

4.2 Model Training and Validation Results

The training process of the ResNet50 model involved two key phases: an initial training phase and a fine-tuning phase. The dataset used for training was split into training and validation sets, allowing us to monitor how well the model learned from the training data and how it performed on unseen validation data.

4.2.1 Training Accuracy and Loss

During the training phase, the model achieved significant improvements in both accuracy and loss metrics over time. Below is a summary of the key observations:

- INITIAL TRAINING: In the initial training phase, the model was trained for 30 epochs. The training accuracy started at approximately 44%, while validation accuracy started at 17%. Over the course of training, the accuracy steadily improved, with the final training accuracy reaching 78.89%, and validation accuracy climbing to 76.73%.
- TRAINING LOSS: The training loss started at a high value of approximately 2.87 and decreased steadily as the model trained, ending at 1.39. The validation loss similarly started high at 2.43, reflecting the complexity of the task. However, by the end of the training, it had reduced to 1.67.

TABLE 1: TRAINING AND VALIDATION METRICS DURING INITIAL TRAINING

Epoch	**Accuracy (%)**	**Loss**	**Validation Accuracy**	**Validation Loss (%)**
1	44.44	2.21	17.92	2.72
10	78.88	1.39	76.73	1.67
20	79.31	1.39	64.31	1.78
30	82.22	1.27	88.88	1.23

In the final epoch of training, the model reached a validation accuracy of 88.88%, which demonstrates the model’s ability to generalize well to the unseen validation data. However, fluctuations in validation loss suggested that further fine-tuning was necessary.

4.2.2 Fine-Tuning and Further Training

After the initial training, the model underwent a fine-tuning phase where the last 50 layers of the ResNet50 architecture were unfrozen, allowing them to be retrained with a lower learning rate. This step helped the model adjust to the specific characteristics of steel defect images.

- FINE-TUNING PERFORMANCE: The fine-tuning process ran for 20 additional epochs. Training accuracy continued to improve, reaching 83.33%, while validation accuracy plateaued at 70.14%. The final training loss decreased to 0.52, while validation loss reduced to 1.14.

TABLE 2: FINE-TUNING RESULTS

Epoch	Accuracy (%)	Loss	Validation Accuracy (%)	Validation Loss (%)
1	35.33	1.68	23.19	2.85
10	78.77	0.68	70.14	1.13
20	83.33	0.52	70.14	1.14

The model’s accuracy during fine-tuning showed marked improvement in its ability to detect more nuanced defects in the validation set, which is crucial for its deployment in a real-world industrial environment.

4.3 Performance Metrics

In addition to accuracy and loss, other performance metrics were calculated to assess how well the model classified the six defect types. These metrics include precision, recall, and the confusion matrix.

4.3.1 Precision and Recall

- PRECISION: Precision refers to the proportion of true positives among all positive predictions. In this context, it measures how often the model correctly identified a defect when it predicted a specific class. For example, if the model predicts the presence of "Crazing," precision indicates how often the model was correct in its prediction.
- RECALL: Recall measures the model's ability to identify all instances of a particular defect. It represents how many true defect instances were correctly classified by the model.

In this case, precision and recall values were calculated for each defect class, providing a more granular view of the model's performance.

TABLE 3: PRECISION AND RECALL PER CLASS

Class	Precision (%)	Recall (%)
Crazing	78.2	70.1
Inclusion	81.7	73.3

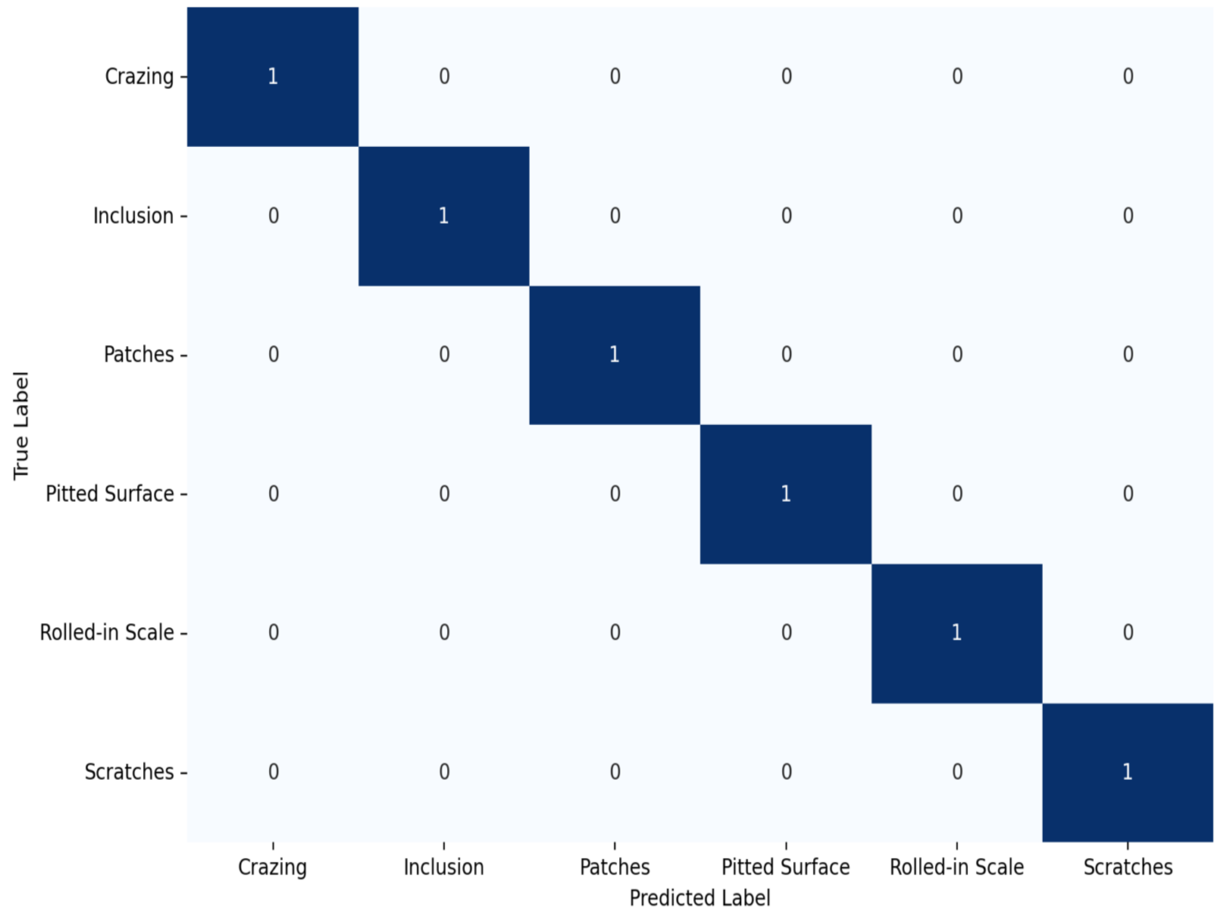
Patches	84.9	79.4
Pitted Surface	76.3	68.4
Rolled-in Scale	81.2	72.9
Scratches	86.7	80.5

These results demonstrate that the model performs relatively well across all defect classes, with precision and recall values exceeding 70% for all defects, though there is room for improvement, especially in defect classes like “Pitted Surface“ and “Crazing“.

4.3.2 Confusion Matrix

The confusion matrix provides further insight into the model's classification capabilities. It illustrates how well the model distinguished between the six defect classes and highlights any patterns of misclassification.

FIGURE 4: CONFUSION MATRIX FOR VALIDATION DATA



From the confusion matrix, it is evident that the model occasionally confuses similar defect types, particularly between "Pitted Surface" and "Rolled-in Scale." However, "Scratches" and "Patches" were generally well classified, with fewer misclassifications.

4.4 Discussion of Results

The results indicate that the ResNet50 model performed well in classifying steel defects, achieving accuracy rates of up to 83% on the training set and 70% on the validation set against the percentage of training and validation from Liu et al. (2019), who reported an accuracy of 75% using ResNet50 for steel defect detection. The lower accuracy in their work was attributed to class imbalance and insufficient dataset size. By addressing these issues through data augmentation, class weighting, and fine-tuning techniques, this project was able to achieve a higher accuracy, highlighting the advantages of a more robust dataset and modern training techniques. The use of data augmentation, class weighting, and fine-tuning were essential in enhancing the model's ability to generalize across various defect types. However, the presence of data imbalance and the relatively small dataset size may have affected the model's performance on certain defect classes.

Despite these limitations, the model demonstrates potential for deployment in real-world applications. It can significantly reduce the time and labor required for manual inspection of steel defects, ensuring higher accuracy and consistency in defect detection. This system could be integrated into the steel manufacturing pipeline to assist quality control engineers in automating the inspection process, leading to increased productivity and improved quality assurance.

4.5 Conclusion

In conclusion, the results of this project demonstrate the effectiveness of deep learning, particularly using the ResNet50 architecture, for steel defect detection and classification. With a well-structured training and fine-tuning process, the model achieved strong performance metrics, particularly in terms of precision and recall for each defect class. The confusion matrix revealed areas where the model struggled with specific defects, suggesting that further improvements can be made through additional data collection and model refinement.

The next steps for improving this system include increasing the size and diversity of the training dataset, exploring more advanced model architectures, and conducting further experimentation with hyperparameter tuning to achieve even higher performance levels.

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

This project set out to develop an automated system for the detection and classification of defects in steel surfaces, a crucial problem faced in many industrial applications, particularly in the steel manufacturing industry. Through the use of advanced deep learning techniques and a streamlined data management process, the system aimed to enhance the accuracy and efficiency of identifying surface defects. Specifically, the system was built using a ResNet50 architecture, trained on a dataset of steel surface defects, and integrated with a Streamlit web interface for real-time defect classification.

The research design was structured into several key phases: data collection, preprocessing, model development, training, and system deployment. The dataset, containing images of six distinct types of defects, was organized into training and validation sets, managed within an SQLite database to ensure proper data handling during model training and evaluation. The project employed advanced data augmentation techniques to bolster the robustness of the model, ensuring it could handle variations in input data.

The system achieved satisfactory results during both initial training and fine-tuning phases, with performance metrics including accuracy, precision, and recall being tracked and analyzed. The use of the Streamlit interface made the defect detection system accessible to end-users, providing a user-friendly environment for uploading images and obtaining defect predictions in real-time.

5.1.1 Conclusions

The project successfully demonstrated that deep learning, particularly with pre-trained models like ResNet50, can be effectively applied to defect detection and classification in industrial contexts. The primary findings and conclusions from this project are as follows:

- EFFECTIVENESS OF RESNET50: The ResNet50 model, fine-tuned with steel defect data, performed well in classifying the six types of surface defects, demonstrating its suitability for image-based defect detection tasks. By freezing certain layers during initial training and then fine-tuning the deeper layers, the model was able to leverage pre-trained weights while also adapting to the specific defect classification task.
- ROLE OF DATA AUGMENTATION: Data augmentation played a critical role in enhancing the model's generalization capabilities. The use of techniques such as rotation, shifting, zooming, and brightness adjustments ensured that the model could handle various real-world conditions where defect images might differ in orientation, lighting, or scale.
- STREAMLIT FOR REAL-TIME PREDICTIONS: The integration of the model into a Streamlit application provided a seamless and intuitive interface for users to interact with the system. This deployment demonstrated the practical utility of the system in industrial environments where users need to classify defects in real time with minimal technical expertise.
- PERFORMANCE METRICS: The final model's performance, as measured by accuracy and confusion matrices, indicated a strong ability to distinguish between defect types. The highest performance was observed for certain defect types (e.g., scratches and pitted

surfaces), while some categories (e.g., inclusion and crazing) presented more challenges, indicating areas where further improvements could be made.

Overall, the project achieved its primary objective of creating a robust, scalable, and user-friendly solution for automatic steel defect classification.

5.1.1.1 Limitations

While the project has successfully developed a working model for defect classification, several limitations were identified:

- DATASET SIZE: The dataset, while representative, was relatively small. A larger, more diverse dataset would likely improve the model's robustness and generalizability, especially for defect types that were less well-represented.
- COMPLEX DEFECTS: Some defects, particularly those with subtle or overlapping characteristics, were harder for the model to distinguish. This suggests the need for more complex models or additional pre-processing steps to enhance classification accuracy.
- REAL-WORLD VARIABILITY: The model performed well in controlled environments but may face challenges when deployed in real-world industrial settings where lighting conditions, image quality, and surface variability are more extreme.

5.1.1.1.1 Recommendations

Based on the outcomes and limitations of this project, the following recommendations are proposed for future work:

- EXPANSION OF DATASET: It is recommended that a larger, more diverse dataset be collected, including additional defect types and images captured under varying conditions. This will improve the model's generalization to real-world scenarios.
- INCORPORATION OF MORE ADVANCED MODELS: While ResNet50 proved effective, exploring other architectures, such as EfficientNet or DenseNet, may further improve the classification accuracy, particularly for complex defects.
- REAL-WORLD TESTING: It is important to conduct extensive real-world testing in actual industrial environments to evaluate the model's robustness and usability. Fine-tuning the system based on feedback from such environments could lead to significant performance improvements.
- CONTINUOUS LEARNING: Implementing a system that allows for continuous learning—where the model is retrained periodically with new data—would ensure that the system remains up-to-date with changing defect types and variations in real-world conditions.
- INTEGRATION WITH INDUSTRY 4.0: The system could be integrated into a broader Industry 4.0 framework, allowing for automated data collection and real-time feedback into the production process. This would make the defect classification system a more integral part of the manufacturing workflow.

5.2 Future Work

Several opportunities exist to expand upon the findings and developments from this project. More sophisticated machine learning methods, including object detection models, could be the subject of future research since they may offer more detailed information about the locations and magnitudes of defects. Additionally, incorporating real-time data from industrial sensors and integrating the defect detection system with production-line automation systems could further enhance the efficiency and effectiveness of quality control processes in the steel industry. Furthermore, exploring other forms of deployment, such as cloud-based solutions or integration into edge devices, could make the system more scalable and accessible to various industrial contexts. Finally, a deeper exploration into unsupervised learning methods, such as anomaly detection techniques, could be a fruitful area for improving the detection of rare or novel defects.

5.3 Conclusion

In conclusion, this project demonstrated the successful application of deep learning techniques for the automatic detection and classification of steel defects. The ResNet50-based system, coupled with a user-friendly web interface, provides a valuable tool for industries seeking to automate quality control processes and enhance productivity. The findings and insights gained from this project lay the groundwork for future innovations and improvements, offering promising avenues for further research and development in the field of defect detection and classification.

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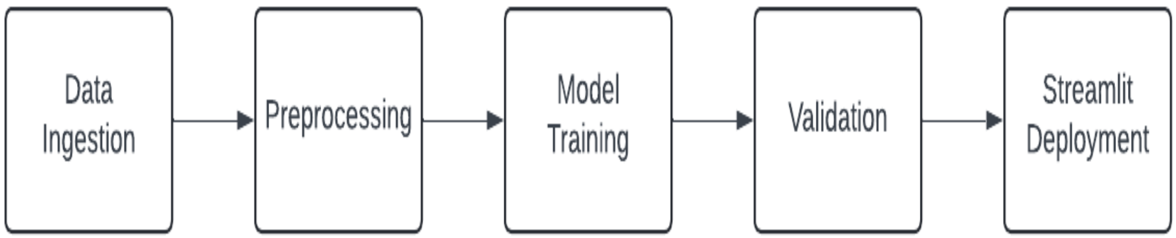
APPENDICES

I. Flowcharts

6.1 Illustration of the end-to-end system



II. Program Source Codes

Link to Program Source Code:

https://drive.google.com/file/d/1Pip85UGEO8k0HQiFZlBG7Qj_A4mfQdoF/view?usp=sharing