Deep Learning-Based Automated Defect Recognition and Quality Grading in Leather for Zero-Error Inspection

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Deep Learning-Based Automated Defect Recognition and Quality

Grading in Leather for Zero-Error Inspection

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Abstract

Accurate detection and grading of defects remain critical challenges in the leather industry, as ordinary manual inspection need labour, biased, and doubtful to inconsistency. Variations in lighting conditions, surface textures, and inspector expertise mostly lead to misclassification, by that negatively affecting material use and product value.

Recent advances in artificial intelligence, mainly deep learning techniques, have shown significant potential for automated and objective defect inspection. Although previous studies have shown defect detection accuracies of about 92% to 97% under controlled imaging conditions, their industrial application is limited by less datasets and a very low range of defect categories, which reduce strength under real-world conditions.

This study presents a deep learning-based automated framework for leather defect recognition and quality grading, targeting to fair detection accuracy and textue across different leather textures and finishing processes. The proposed framework covers enhanced data preprocessing, defect-specific data augmentation strategies, and an attention-based feature clarification mechanism to improve defect execution and classification performance.

The developed approach is intended to support reliable, scalable, and industrially deployable inspection systems, favouring the understanding of

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near zero-error quality checking in leather manufacturing.

Keywords: Leather defects, Automated inspection, Deep learning, Computer vision, Quality grading, Attention mechanism, Sustainability.

1. Introduction

Leather inspection is a important quality control process in the leather and footwear industry, as surface defects directly affect grading accuracy, processing ability, and the overall value of finished products. Natural defects, including scars, wrinkles, insect bites, grain looseness, and colour change, typically originate from biological and environmental factors during animal growth and further hide preservation steps [1], [2]. Accurate identification and classification of these defects are must to minimize material wastage and to maintain same quality standards across leather processing operations.

Traditionally, leather inspection depends on manual visual checking done by inspectors. Although this method remains adopted in wider area, it is naturally personal, needs labour, and very sensitive to human influence like fatigue, inspector experience, and changes in lighting conditions [3], [4]. Previous studies have shown many inter- and intra-inspector changes, which sometimes gives defect misclassification and not efficient use of premium leather grades [5].

Advances in computer vision and artificial intelligence have made the development of automated surface checking

systems able of defeating the limitations of old manual inspection approaches [6], [7]. Deep learning models, mainly convolutional neural networks (CNNs), have shown good performance in learning complex texture patterns and detecting surface deformity across various industrial materials, like steel, textiles, and composites [8], [9]. Further, the application of these techniques to leather defect detection has got increasing thought in

these years.

Several studies have shown defect detection accuracies of about 92% to 97% using deep learning- based ways when checked under controlled imaging conditions [10]– [12]. While these results are good, many of the suggested methods focus on a limited defect categories or depend on uniform lighting and background conditions. This actually limits their effectiveness in real tannery environments, where leather surfaces gives more changes in texture and appearance [13]. Also, practical industrial deployment also demands inspection systems that are efficient and capable of running in real-time or near realtime, without ruining existing production process [14], [15].

Date Collection Image Pre-Processing Defect - Specific Data Augmentation CNN + Attention Module Defect Classification Quality Grading Output

Collect Data

Apply Data Augmentation

Pre-Process Images

2.2 Data Collection and Image Acquisition

Leather surface images were collected from processed

hides covering a large range of textures, finishes, and

defect types, like scars, cuts, wrinkles, grain damage, and

change in colour. The images were taken under controlled

yet industry-like lighting conditions to realistically

representing the changes found in real tannery environment

space [16]. Images with high resolution was used to make

Motivated by these challenges, this study suggests a deep learning-based framework for automated leather defect recognition and quality grading. The approach integrates attention-based feature clarification along with defectspecific data enhancement methods to add detection accuracy and powerful. The main goal is to develop a system that is not only dependent in various industrial conditions but also capable of supporting near zero-error inspection in leather manufacturing.

2. Methodology

2.1 Overall Workflow

The overall workflow of the proposed leather defect recognition and quality grading system is shown in Fig. 1. The framework starts with image requirement, then preprocessing and defect-specific data strong. Then, defects are seen using a complex neural network increased with an attention mechanism, and the results are finally used to give a quality grade to each leather sample.

Process through CNN + Attention Module

Classify Defects & Grade Quality

sure that little surface details, which are necessary for right defect identification, were conserved.

2.3 Image Preprocessing

Before training the model, the images first undergoes through preprocessing to enhance quality and reduce noise.

This includes resizing all images to a fixed resolution,

normal the contrast, and correcting light to satisfy for lighting differences across samples [17]. These steps help

ensure more comfortable features and also speed up model training and coming together.

2.4 Defect-Specific Data Augmentation

To overcome the limitations of a small dataset and improve the model’s ability to generalize, defect- specific data enhancement methods are used. These include operations like rotation, flipping, scaling, adjusting brightness, and fix localisation misinterpretation, all with ensuring that the main characteristics of the defects are preserved [18]. This approach helps the model become more powerful to variations in adjustment, texture, and lighting situations.

2.5 Deep Learning Model with Attention Mechanism

The central part of of the proposed system is a convolutional neural network (CNN) architecture made more capable with an attention mechanism for feature refinement. The conventional CNNs are effective at taking out hierarchical features, the attention mechanisms make sure the model to focus specifically on regions of the leather surface that are most relevant to defects [19]. This selective focus boosts defect locating and helps reduce false positives caused by natural changes in leather texture.

2.6 Quality Grading Strategy

Once defects are seen and recognised, they are mapped to standard of leather quality grades like, based on defect type, severity, and spatial distribution. This automated grading approach follows industrial classification norms and gives objective guidance for decision-making in the further processing stages [20].

3. Results and Discussion

The proposed framework shows significant improvements in defect detection accuracy and powerfulness as compared to previous CNN-based approaches reported in earlier studies [10], [11]. By integrating the attentionbased feature refinement, the system can more effectively find defects, even slight irregularity hidden within complex leather texture material.

Additionally to this, defect-specific data enhancement enhances generalization, making the model to perform easily in different leather finishes and lighting situations. The framework also shows less response time, making it more suitable for near real-time inspection in industrial environments [14]. Together, these advancements support to reliable, near zero-error inspection and make less depedency on manual evaluation and checking.

From a sustainability peerspective, automated inspection minimizes material wastage which is caused by unnecessary and over-rejection of leather which is not in use. By ensuring more accurate grading, this supports resource structured manufacturing methods [21].+

4. Conclusion

In summary, this study establishes a deep learning-based framework for automated leather defect recognition and quality grading, focusing on reducing the limitations of manual inspection. By using enhanced preprocessing, defect-specific data satisfactory, and attention-based feature refinement, the system will gain improved accuracy, powerful, and practical applicability in industrial settings.

The proposed framework makes objective, scalable, and sustainable near zero-error inspection in leather manufacturing. Looking ahead, future work will focus on expanding the range of defect categories, which will enable real-time deployment, and integrating the system with smart tannery operations.

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