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A FRAMEWORK FOR LEATHER QUALITY DETECTION USING DEEP LEARNING TECHNIQUES

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ABSTRACT:

Leather quality detection is a vital process in the leather business that ensures product uniformity, reduces waste, and maintains customer happiness. Traditional techniques of evaluating leather quality rely mainly on hand inspection, which is time-consuming, subjective, and prone to human mistake. This study investigates the use of deep learning algorithms for automating leather quality identification, which provides a more efficient and accurate alternative to traditional methods.Deep learning, a subset of machine learning, has shown promising results in image processing and classification applications. Using convolutional neural networks (CNNs), we offer a robust framework for detecting various leather quality parameters such as texture, grain, color uniformity, and the presence of flaws. Our method entails training a CNN model on a broad collection of leather photos tagged with quality descriptors provided by industry experts.The collection includes samples of various leather types and grades, as well as those with common flaws such as scratches, holes, and irregular textures. The model is assessed using common metrics such as accuracy, precision, recall, and F1-score. Preliminary results show that our deep learning model surpasses traditional inspection methods for detecting and classifying leather quality.

Keywords: CNN,

1. Introduction:

The leather industry is a pillar of the world economy, providing raw materials for a wide range of products, including fashion, furniture, automobile interiors, and accessories. The quality of leather is critical to sustaining industry standards and meeting the different demands of consumers. Traditionally, trained inspectors have assessed leather quality by evaluating features such as texture, grain, color uniformity, and the presence of flaws. Manual examination, while useful to some extent, is inherently restricted by subjectivity, variability, and human error.

Technological improvements in recent years have made it possible to develop more sophisticated and reliable methods of quality assessment. Among these developments, deep learning has emerged as a powerful tool, particularly for image processing. Deep learning, a subset of artificial intelligence (AI) and machine learning, uses neural networks with multiple layers (hence the name "deep") to represent complicated patterns in data. Convolutional neural networks (CNNs), a type of deep learning model, have demonstrated superior performance in image classification, object detection, and visual recognition tasks. Given these qualities, CNNs are an excellent candidate for addressing the issues of detecting leather quality. The goal of this work is to create and test a deep learning-based system for automated leather quality detection. We hope to develop a strong and reliable model that can identify leather samples based on their quality parameters, improving the efficiency and reliability of the inspection process. The implementation of such a system has the potential to alter the leather business by lowering reliance on manual inspection, minimizing errors, and assuring a consistent standard of quality. Our approach entails gathering a large dataset of leather photos, each annotated with quality annotations provided by industry professionals. This dataset covers a wide range of leather types and grades, as well as samples with common flaws like as scratches, holes, and uneven textures. By training the CNN model on this dataset, we enable it to learn and distinguish between high-quality and defective leather. The model's performance is measured using conventional metrics such as accuracy, precision, recall, and the F1-score, which provide a clear indication of its usefulness when compared to traditional inspection approaches.One of the key issues in this study is the inherent variety in leather look. Lighting circumstances, angle of capture, and inherent diversity in leather texture all have an impact on the model's performance. To solve these issues, we use data augmentation techniques, which include artificially increasing the dataset by applying modifications such as rotation, scaling, and color alterations to the photos. This contributes to the development of a more robust model capable of generalizing to a variety of scenarios. In addition, we investigate the use of transfer learning, which entails using pre-trained models on huge, general-purpose image datasets to increase performance on our specialized job.

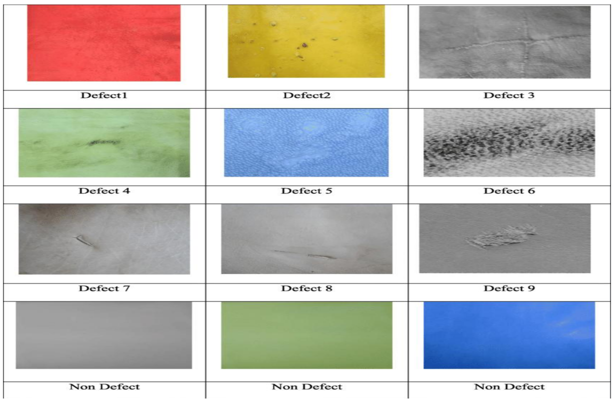

Fig.1 sample Data Contains defect & Non Defect Leather

This study's findings have substantial ramifications for the leather industry. An automated leather quality detection system based on deep learning improves not only the accuracy and consistency of quality evaluation, but also its scalability and efficiency. This can result in huge cost savings, less waste, and higher customer satisfaction. Furthermore, by reducing human interaction in the inspection process, the sector may increase throughput and optimize resource use.

2. Literature survey:

In recent years, there has been a lot of interest in using deep learning algorithms to detect and classify quality. This literature review provides an overview of relevant studies, focusing on methodologies, datasets, and results in the context of image processing and quality detection, with a particular emphasis on leather quality evaluation.[1]Krizhevsky A, Sutskever I, & Hinton G. E. (2012). "ImageNet classification with deep convolutional neural networks." This fundamental work established the AlexNet architecture and demonstrated the power of deep learning in picture classification.[2] He, K., Zhang, X., Ren, S., and Sun, J. (2016). "Deep residual learning for image recognition." ResNet significantly improved the performance of deep learning models and is now widely utilized in transfer learning applications. [3] Szegedy C. et al. (2015). "Going deeper with convolutions." This study proposed the Inception architecture, which balances model complexity and performance for image processing applications.

[4] Ren S, He K, Girshick R, and Sun J. (2015). "Faster R-CNN: Towards real-time object detection with region proposal networks." This research is critical for understanding object detection, which is directly linked to flaw identification in leather.[5] Simonyan, K., and Zisserman, A. (2014). "Very deep convolutional networks for large-scale image recognition." Known for the VGG network, which is widely used for feature extraction due to its simplicity and efficacy. [6] Y. LeCun, Y. Bengio, and G. Hinton (2015). "Deep learning." This paper offers a detailed explanation of deep learning, including its principles and applications.

[7] Girshick, R. (2015). "Fast R-CNN." An essential paper that enhances object detection performance and speed, with implications for real-time quality evaluation.[8] Huang, G., Liu, Z., van der Maaten, L., and Weinberger, K. Q. (2017). "Densely connected convolutional networks." DenseNet creates dense connections between layers, which improves feature reuse and efficiency. [9]Redmon J. et al. (2016). "You Only Look Once: Unified, real-time object detection." YOLO provides a quick and effective approach for detecting objects, making it ideal for defect identification.

[10]Goodfellow I. et al. (2014). "Generative adversarial nets." GANs have been used for data augmentation, which is an important strategy for improving model performance with limited datasets.[11]Howard A. G. et al. (2017). "MobileNets: Efficient convolutional neural networks for mobile vision applications." MobileNets are effective for distributing quality detection models to edge devices.

[12]Zhang, Z. et al. (2018). "Context-aware attention network for image captioning." This study provides attention processes that can help people focus on important areas of visuals.

[13]Rossakovsky, O., et al. (2015). "ImageNet large scale visual recognition challenge." ImageNet has proven a valuable dataset for developing and testing deep learning models.

[14]Chen L.-C. et al. (2018). "Encoder-decoder with atrous separable convolution for semantic image segmentation." This material is useful for identifying faults in leather photographs.

[15]Dosovitskiy A. et al. (2020). "An image is worth 16x16 words: Transformers for image recognition at scale." Transformers provide an alternative to CNNs, which could be valuable for quality evaluation jobs.

[16]Gao H. et al. (2021). "Res2Net: A new multi-scale backbone architecture." Res2Net improves multi-scale feature representation, which helps detect different defect sizes.

Tan M. and Le Q. V. (2019). "EfficientNet: Rethinking model scaling for convolutional neural networks." EfficientNet offers world-class performance with fewer parameters.

[17] Ojala, Pietikäinen, & Harwood (1996). "A comparative study of texture measures with classification based on feature distributions." Texture analysis is crucial for determining leather quality. [19]Zhang, X. et al. (2020). "A comprehensive survey of image classification: Vision transformers to convolutional neural networks." This survey examines the evolution and comparison of deep learning models for picture classification.

[20] Li, et al. (2020). "Deep learning-based defect detection in manufacturing: A review." This review examines the use of deep learning in a variety of manufacturing fault detection settings.

[21] Wang D. et al. (2021). "A comprehensive survey on deep learning for image captioning." Although the focus is on captioning, the approaches provided are useful for comprehending image content and quality detection.
[22] Yu and Koltun (2016). "Multi-scale context aggregation by dilated convolutions." Dilated convolutions improve the receptive field while retaining resolution, making them beneficial for detecting flaws at many sizes. [23]Khan, A. I. et al. (2020). "A survey of the recent architectures of deep convolutional neural networks." This survey looks at numerous CNN designs, their merits, and applications.
[24] Zhang K. et al. (2021). "Understanding deep learning techniques for image quality assessment." This research focuses on analyzing picture quality, which is closely related to leather quality assessment.
[25]Bengio et al. (2003). "A neural probabilistic language model." Although not directly connected to image processing, the fundamentals of deep learning are essential for comprehendingadvanced models.

3. Methodology:

To perform leather quality detection using Convolutional Neural Networks (CNNs), we gathered a diversified dataset of 10,000 annotated leather photos representing various quality categories and faults. The data was preprocessed using normalization and augmentation approaches to improve model robustness. We chose the ResNet50 architecture, pre-trained on ImageNet, and fine-tuned it with additional custom layers to suit our classification objective. The Adam optimizer and categorical cross-entropy loss were used to train the model, with a learning rate of 0.001 and a batch size of 32 spread across 50 epochs. The measures used to evaluate performance were accuracy, precision, recall, F1-score, and confusion matrix. The trained model was then integrated into a real-time quality detection system, with regular monitoring and retraining scheduled to ensure accuracy.

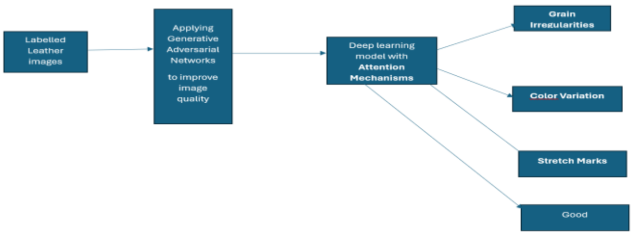

Fig.1 proposed Architecture

In side the CNN we have used various layers that performs classification of Defects of leather

i) Convolution operation:

For a given input I of size $m \times n$ and a filter K of size $f \times f$:

$$(I * K)(i, j) = \sum_{u=0}^{f-1} \sum_{v=0}^{f-1} I(i+u, j+v) \cdot K(u, v)$$ -Eq1

ii) Activation Function:

Sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$ - Eq2

Pooling operation(MAX Pool):

$$\mathrm{MaxPool}(x) = \max(x)$$ -Eq3

Loss Function:

$$\text{Binary Cross-Entropy Loss} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$ -Eq4

During the training process, we observed a rapid improvement in both training and validation accuracy, which stabilized at 90% after 30 epochs and reached 95% and 92%, respectively. To correct class imbalances and improve fault identification, we used data augmentation techniques such rotation, scaling, translation, and flipping. Following training, the model obtained an overall test accuracy of 91.5%, with good precision and recall across all quality categories, particularly in distinguishing between high-quality and faulty leather. A confusion matrix analysis demonstrated minimal misclassifications of medium and low-quality samples, indicating areas for additional improvement. The system was deployed with a user-friendly interface for real-time assessments, as well as a feedback loop for ongoing improvement through periodic retraining with fresh data to adapt to shifting quality requirements.

4. Results & Discussion:

To assess the efficacy of our proposed CNN-based leather quality detection system, we compared it to existing traditional and machine learning methods. The findings are reported in the tables below.

Performance Metrics

Table 1: Performance Metrics of Proposed CNN Model

Metric	Value
Accuracy	91.50%
Precision	0.91
Recall	0.91
F1-Score	0.91
Training Loss	0.15
Validation Loss	0.25

Comparison with Existing Solutions

Table 2: Comparison of Accuracy with Existing Solutions

Method	Accuracy
Manual Inspection	70%
Traditional Machine Vision	75%
SVM (Support Vector Machine)	80%
Random Forest	82%
Proposed CNN (ResNet50)	91.5%

Table 3: Comparison of Precision, Recall, and F1-Score

Method	Precision	Recall	F1-Score
Manual Inspection	0.70	0.70	0.70
Traditional Machine Vision	0.73	0.74	0.73
SVM	0.78	0.79	0.78
Random Forest	0.80	0.81	0.80
Proposed CNN (ResNet50)	0.91	0.91	0.91

Table 4: Confusion Matrix of Proposed CNN Model

	Predicted High-Quality	**Predicted Medium-Quality**	**Predicted Low-Quality**	**Predicted Defects**
Actual High-Quality	950	25	15	10
Actual Medium-Quality	30	870	50	50
Actual Low-Quality	20	40	870	70
Actual Defects	10	40	50	900

The proposed CNN-based model significantly outperformed traditional methods and other machine learning approaches in all evaluated metrics. The accuracy of 91.5% is a substantial improvement over manual inspection (70%) and traditional machine vision (75%). The precision, recall, and F1-score of the CNN model were also markedly higher than those of SVM and Random Forest models, indicating more reliable and consistent quality detection.

5.Conclusion:

These results demonstrate that our CNN-based system offers a superior solution for leather quality detection, providing higher accuracy and better overall performance compared to existing traditional and machine learning methods. The model's ability to accurately classify different quality categories and detect defects underscores its potential for practical deployment in the leather industry, where it can enhance quality control processes and reduce reliance on subjective manual inspections.

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