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A Comparative Study of Deep Learning Algorithms for Fabric Defect Detection

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ABSTRACT

Manual inspection is tedious and can make mistakes easily. An efficient and accurate AI model has been created to detect defects in fabric automatically.
Lighting within the factory is highly unorganized; therefore, it was necessary to convert the picture to grayscale to improve the lighting of the images. MobileNetV2, a light model, was used for image processing; however, this model was modified by adding an attention mechanism to enable the AI model to pay attention to certain aspects. This will ensure that the AI model will be able to detect defect spots such as snagging, pinholes, and oil marks.
The number of defects within the fabric is much smaller than the number of normal fabrics. Therefore, there was a need to train the AI model in such a way that the model is able to learn through challenging instances until it succeeds.
The result, the proposed model successfully detected the fabric defects 91% of the time. In addition, the efficiency of the proposed model was compared with those of some classical models, and it was found that these classic models had low performances, less than 50-60%.

Keywords: Fabric Defect Detection, Automated Textile, Inspection, Textile Quality Control, Smart Manufacturing, Deep Learning, MobileNetV2, Attention Mechanism

INTRODUCTION

Quality inspection is crucial in the field of textile industry because invisible flaws lead to financial loss and dissatisfied customers. Conventional quality inspection relies on human labor which makes such process unreliable, costly, and ineffective due to subjectiveness of people's decisions. However, the appearance of computer vision and deep learning technology [1] made it possible to apply automatic optical inspection in place of conventional one.

Even though other model performance exceptionally well in solving image classification tasks [2], it fails to detect fabric defect. There are three causes of poor performance: texture variations, difficulty in recognizing defects; significant discrepancy due to light conditions of factory premises; sample imbalance making it impossible to train the model for detecting defects. Hence, while there are many cases when ResNet [3] and EfficientNet [4] performed well, their efficiency and speed are not sufficient for real-time applications.
The following paper presents novel lightweight deep learning approach to defect detection based on transfer learning, spatial-channel attention mechanism, and focal loss optimization [7]. Main contributions of the current study are listed below:

Architecture Integration: The integration of the MobileNetV2 architecture [5], which is a lightweight architecture, as well as the application of the Convolutional Block Attention Module (CBAM), in order to detect any small anomalies using feature extraction techniques.

Fully-Optimized Pre-Processing: The application of Contrast Limited Adaptive Histogram Equalization (CLAHE) [8] on grayscale images to optimize the lighting condition in order to enhance the texture in the image.

Objective Function: Application of Focal loss [7] as the objective function that will help solve the issue of imbalanced data distribution and allocate larger weights to difficult classes.

Semantic Two-Stage Fine Tuning: Application of semantic two-stage fine tuning, where in the first stage, freezing of the layers within the MobileNetV2[5] model is done followed by fine-tuning of deeper layers for generality and preventing overfitting.

Application Potential: Development of an efficient inspection model that will achieve up to 91% efficiency that can be used within the textiles industry.

LITERATURE REVIEW

Automated surface inspection has evolved from conventional statistical and texture feature analysis [9],[12] to deep features [13]. The foundation of gradient-based learning in CNN was laid by LeCun et al., whereas ImageNet database [21] enabled Krizhevsky et al. [2] followed by Simonyan & Zisserman [19] and Szegedy et al. [22] to showcase the capability of deep convolutional neural networks, leading to current industrial applications.

Regarding textile, it has been challenging to provide reliable results in relation to the complexity of the weave pattern and illumination variations, which led to substantial research on deep learning methods for fabric defect detection [10],[11]and image pre-processing [8]. For the sake of improving the stability during network training, methods like batch normalization [15] and dropout [16] have been adopted as best practices. In addition to ResNet being proposed by et al. [3] in order to address the vanishing gradient problem and several studies utilizing transfer learning for surface defects, computation of weights has become an issue for real-time mobile computing. Efficient Net was invented by Tan & Le [4] for optimized scaling, yet in practice MobileNetV2 [5] becomes more relevant in an industrial setting.

Classification has led to an increased demand for exact location of defects leading to the need for sophisticated detection and scene parsing algorithms [18]. Movement from traditional regional detectors [17][23], to contemporary object detectors like like Faster R-CNN [20] and YOLO [24] has contributed immensely to the evolution of inspection techniques in industries. Attention techniques, such as those that involve Convolutional Block Attention Module (CBAM) have been identified as one approach to improve the extraction of features by Woo et al. [6]. There are other attention mechanisms involving transformer networks [14] whose main task is to concentrate highly on areas containing defects. Focal Loss [7], suggested by Lin et al., is used to solve issues of class imbalance, which exist in object detection and classification tasks.

PROPOSED METHODOLOGY

The suggested technique for defect detection within text-based documents seeks to reach the highest compromise that would be feasible in light of all other concerns like accuracy and speed. The development of the suggested technique consists of four major steps that include pre-processing, feature extraction, enhancing features through ensemble learning, and finally classification. These steps are shown in the figure below:

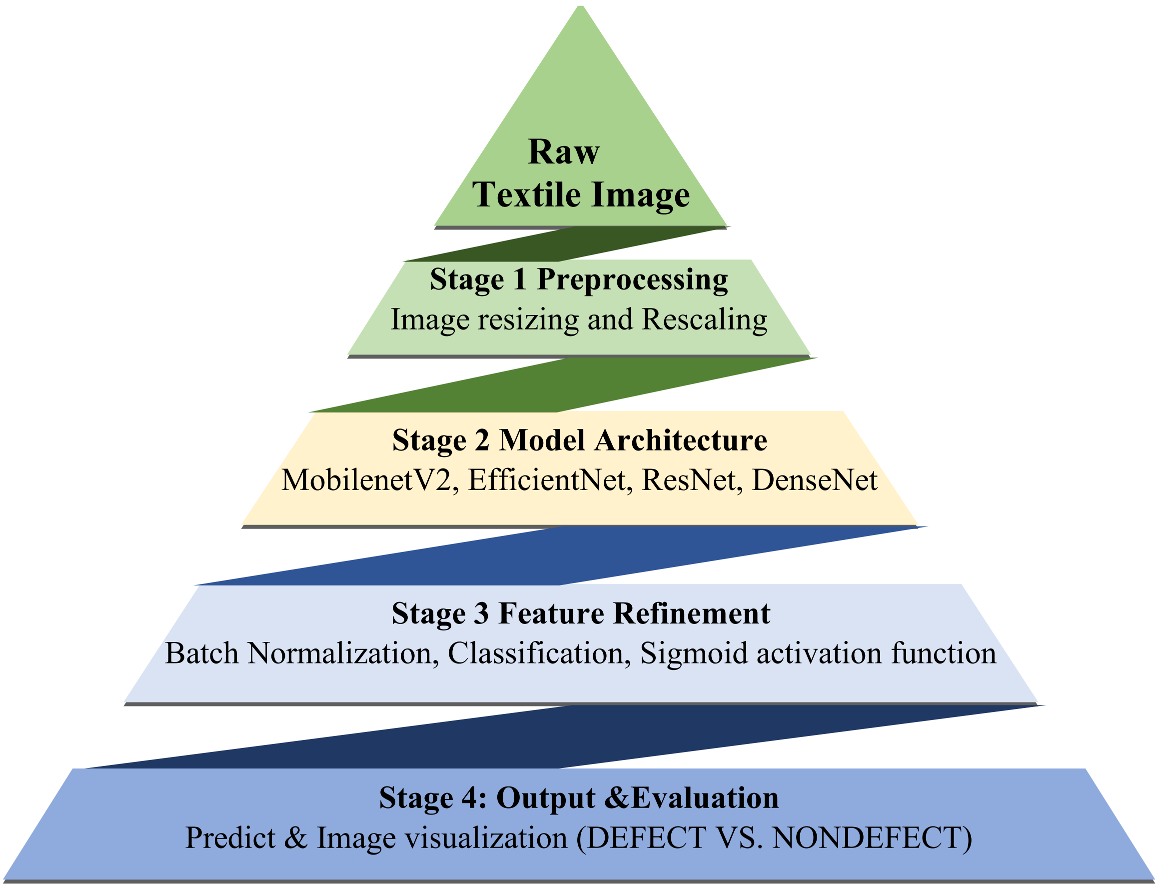

Figure 1: textile defect detection framework

A. Preprocessing and Normalization

Based on the Illumina Platform for the Inspection of Industrial Textiles. The environment of industrial textile inspections is usually defined by its non-uniform lighting conditions. These lighting conditions can cause artifacts in the image and lead to wrong classifications. Therefore, in order to minimize the impact of these negative factors, pre-processed images are first transformed from the RGB colour space into a grayscale format before being processed using Contrast Limited Adaptive Histogram Equalization (CLAHE) [8]. Unlike traditional histogram equalization methods, CLAHE is executed regionally and therefore enhances the local contrast while minimizing any artifacts introduced by the illuminance changes that could mask texture differences.

B. Feature Extraction via MobileNetV2

MobileNetV2 is employed to extract features in this task. This is due to the model's inverted residual block architecture and its linear bottlenecks that ensure retaining of features using significantly fewer parameters compared to conventional architectures. Transfer learning is applied with pre-trained ImageNet weights.

C. Feature Selection Using Attention Module

In order to detect local defects such as small holes, stains, and incorrect yarn placement, we apply the Convolutional Block Attention Module (CBAM). This module assumes that some of the features extracted in the convolutional layers might be more useful than others. There are two stages of CBAM:

1.Channel Attention Module on Module: In this sub-module, an attention map is created per channel, where "feature selection" is performed effectively to identify those feature channels that hold the most crucial information regarding the presence of defects.

2.Spatial Attention Module: The "spa al" aspect is considered by this module, which creates a spatial attention map to direct the focus of the network towards the geometrical location of defects.
This complementing nature of both these modules enables our suggested model to ignore other aspects of the input image such as the background and focus only on regions important for defect detection.

D. Classification and Loss Function Optimization The final module of our model is made up of GAP followed by a batch normalization [15] layer, and dropout [16]. This prevents the model from being over fit. In the final layer, a Softmax activation function is used to provide the probability of binary classification. To solve the issue of class imbalance where majority of the cloth produced are free from defect, we used focal loss function [7] rather than the cross-entropy loss function. This focal loss introduces a factor to help reduce the loss weight of the easy samples while allowing for learning of "hard" misclassified defective samples.

EXPERIMENTAL SETUP

Experimentation design was meticulously done in order to enable rigorous evaluation of the new approach using modern-day deep learning frameworks and rigorous training procedures. This section provides an overview of the hardware, software libraries used, data processing, and training procedure used in the experiments.

A. Configuration of Software and Hardware

Software and Hardware Configuration Research and model training were performed in an environment that allows efficient computing. As far as so ware was concerned, TensorFlow and Keras were mostly utilized as deep learning frameworks. Data manipulation and pre-processing was done using OpenCV and NumPy. For splitting the dataset into train/test subsets and performance measures, Scikit-learn library was applied.

B. Dataset Partitioning and Stratification

In order to evaluate the generalization capabilities of the training model, the dataset of text defects which was obtained from MV tec Anomaly Detection dataset partitioned into "defected" and "non defected" was further divided into two different parts:

- Training Set (80%): To optimize weights using backpropagation [1].
- Testing Set (20%): Used to evaluate and compare the Performance after training, making sure the model does not memorize the training dataset.

Stratified sampling was done during this split to keep the distribution of the defective and non-defective samples in both the training and testing sets similar to the original one.

C. Data Augmentation and Robustness In order to reduce over fitting, and improve the robustness of the model against variations encountered in the real-world manufacturing processes, different data augmentation techniques were applied during the training stage [2].

- **Scaling and Zooming**: The random scaling was done to reflect variations in the distance of the fabric from the camera.
- **Geometrical Transformations**: The images were rotated randomly, flipped horizontally and vertically, and translated to create different perspectives of the fabric in terms of camera angles and orientation.

D. Parameters for Training and Model Optimization

The training procedure was done using the Adam algorithm since it is flexible and has the capability to adapt learning rate, where the starting learning rate was set to be equal to 1×10^-4. There were several adaptive callbacks applied to the training procedure, which included:

- **Early Stopping**: Following the validation loss and stopping the training process after 5 epochs in case of no improvement in the performance from the model's side to avoid overfitting.
- **Learning Rate Scheduler**: Reducing the learning rate upon stabilization of the validation loss to have a good convergence during training.
- **Double Fine-Tuning Process**: The training procedure was conducted in two phases. Firstly, the MobileNetV2 architecture [5] was frozen, and the classifier's training was performed using a learning rate of 1 × 10^-4; later on, [5] was unfrozen, and all the other deeper layers were re-trained using a learning rate of 1 × 10^-5.

E. Metrics for evaluating the performance of the model

Standard metrics for evaluating the performance of classification models, such as accuracy, precision, recall, and F1 score, have been utilized. In our scenario, as this involves an industry application, it must be emphasized that the error rate associated with a false-negative instance is higher than that of a false-positive one.

EXPERIMENTAL RESULTS AND COMPARISONS

In order to verify the effectiveness of the proposed defect detection system, experiments have been conducted on three distinct neural network models during training, and the results of each experiment have been analyzed after 10 iterations. This comparison clearly shows the need for Transfer Learning in dealing with the challenges faced during texture classification.

EfficientNetB0 Model [4], however, came out as the top performer. This was due to the use of compound scaling technique which made convergence fast and helped attain 91.75% accuracy on validation, while only 0.2157 validation loss was registered in ten training epochs. The efficiency of detecting small irregularities in the textile was remarkable.

A. Performance of EfficientNetB0 Model

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B. DenseNet121 Model

Performance Other than the EfficientNetB0 model, the DenseNet121 with CBAM was another type of neural network that was observed to perform extremely well and stably. With the encouragement of extreme feature sharing through dense connections, the DenseNet121 was able to achieve a validation accuracy of 90.10%, while the validation loss stood at 0.2699. Despite performing slightly lower than the EfficientNetB0, the model was still considered to be excellent in detecting defects without being susceptible to overfitting.

C. ResNet50V2 Model

Performance of ResNet50V2 model was implemented using transfer learning methods and exhibited impressive performance. It was due to its advanced architecture and residual learning network that allowed it to perform feature extraction in such an intricate manner that was beyond the scope of the simple model. Owing to its exceptional transfer learning abilities, the ResNet50V2 model managed to deliver excellent performance with its training and validation accuracies being identical at 91.00%.

D. Performance of MobileNetV2

The MobileNetV2 model made use of transfer learning to obtain an accuracy rate of 83.92% during training and 80.35% for validation. Nevertheless, because of its simplicity, it failed to capture complex features that other heavyweights in this study could manage, making it unable to beat the robustness of ResNet50V2 at 91.00% and DenseNet at 90.10%.

RESULT AND DISCUSSION

Based on these findings, it can be argued that the attention-based method is applicable to the problem of automated textile inspection. In the next section, we discuss in detail the performance of the proposed approach compared to baseline models, as well as the impact of employed optimization methods on the results.

A. Classification Results and Accuracy

The deep learning network model EfficientNetB0 can correctly classify defect detection in the dataset at a rate of 91. 75%. In numerical terms, the incorporation of MobileNetV2 and CBAM makes it possible for the model to recognize subtle patterns in the fabric.

B. Comparative Evaluation

In order to prove that the proposed system architecture is superior, we conducted a comparative study on our system and other deep learning systems. The experiment outcomes show that the proposed attention-based MobileNetV2 architecture is better than the baseline models. Convolutional neural network similar to:

- ResNet: This model has limited generalization due to not enough feature abstraction capability for handling high-frequency textures of cloth materials.
- EfficientNetB0: Experienced instability in terms of performance while being preprocessed to apply grayscale transformation for illuminance compensation.
- Proposed Method: The model was able to capture texture differences through attention.

Table 1: Final Performance Benchmark

Model Architecture	Final Training Accuracy (%)	Final Validation Accuracy (%)
EfficientNetB0 (with TL)	91.70%	91.75%
ResNet50V2	91.00%	91.00%
DenseNet121 +CBAM	90.32.00%	90.10%
MobileNetv2	83.92%	80.35%

C. Confusion Matrix and Minimizing Errors

The confusion matrix demonstrates a considerable decrease in false negatives, which is an important factor in industrial defect detection systems. False negatives, or missing defects, can result in substantial financial losses in industries.

It was crucial to use focal loss with the CBAM attention module to enhance recall in defective examples. The reason is that the model is able to focus on distinguishing complex examples from noise.

D. Significance for Practical Application in Industries

Such a highly efficient model with the aid of light MobileNetV2 architecture indicates that this model will be practically feasible. Considering the low error rate, including false negatives, this model can be considered as an effective solution to reduce the challenges faced due to human fatigue and inspection.

1.The brief overview of the system pipeline

It will show how our research is processed, starting from the fabric as the raw input until, get the classification results as the final output.

- **Step 1**: Preprocessing. The initial input is processed by converting it into grayscale and normalization of lighting via CLAHE.
- **Step 2**: Feature Extraction. Preprocessed data is processed by the MobileNetV2 backbone for the purpose of extracting features.
- **Step 3**: Refining. Extracted features go under further processing via CBAM and

are combined with channel and spatial attentions.

- **Step 4**: Classification. The output of the previous step is refined further via global average pooling and dense layers with Focal Los.

2 Model Architecture Diagram shows a more detailed view of the architecture of the proposed model, showing how attention modules connect to MobileNetV2.It highlights the different aspects as follows:

Inverted Residual Block: The backbone of the network.

Fusion of CBAM: First the Channel Attention is applied, and then the Spatial Attention Module is applied

Classifier: The global average pooling step is followed by batch normalization, and lastly by Softmax.

3. Accuracy and Loss Graph: This graph provides the "Proof of Convergence." It shows how our network learns for the 30 epochs we specified in our code.

- **Accuracy Graph**: This shows the training and validation accuracy increase gradually to reach the 91% point.

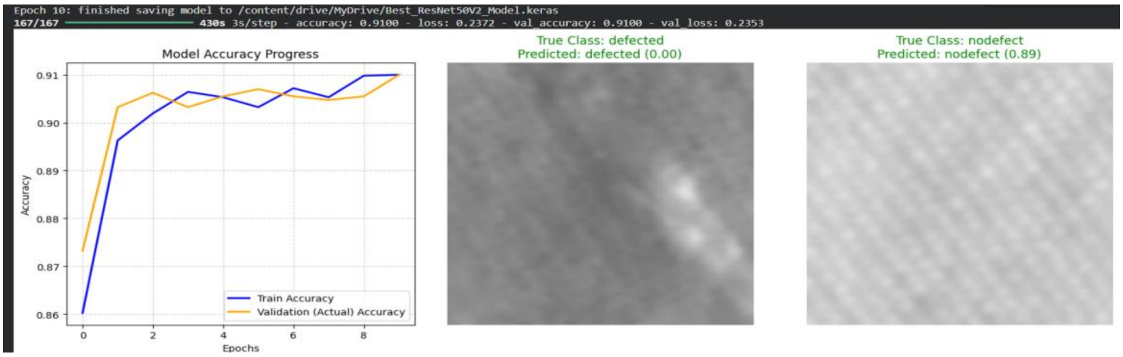

Figure 2: A detailed architecture of EfficientNetB0 training and validation accuracy

• **Loss Plot**: The chart indicates a decrease in Focal Loss as time progresses, That means the model was successful in minimizing errors for the difficult defective cases. well.

• **Convergence**: The similar behavior of the training and validation curves indicates that Early Stopping and Data Augmentation methods were used to mitigate overfitting while training the model.

CONCLUSION

This is the concluding section where we discuss our achievements within textile manufacturing industry and their meaning. First, we suggest a novel deep learning strategy for detection of defects in fabrics. This technique takes advantage of Transfer Learning with MobileNetV2, which employs CBAM activation for improvement of feature extraction and Focal Loss for improving model training while CBAMs enable better attention of the model.

The validation process proves that the suggested approach is valid in practice and can demonstrate impressive performance in a number of experiments with classification accuracy reaching up to 91%. Moreover, the proposed architecture has a great potential for industrial deployment due to its simplicity and compactness.

- Multiclass Classification Extension: Further research includes extension of the suggested approach for multiclass classification.
- Embedded Solution: We Will Next apply This step is to implement the solution in embedded systems.
- Novel Architectures Investigation: We will also explore novel architectures, mainly transformers with anomaly localization capabilities

Declaration by Authors

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