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FUSIONDEFECTNET-A CNN VISION TRANSFORMER METHOD WITH ADAPTIVE GATING FOR EXPLAINABLE TEXTILE DEFECT DETECTION

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ABSTRACT

It is challenging for textile manufacturers to automate inspection due to a pronounced imbalance in the class of samples, with the majority of samples being defect-free, and the complementary nature of local and global defects. In this study, FusionDefectNet is presented as a novel hybrid architecture. For extracting local features, Convolutional Neural Networks (CNNs) are used, and for understanding global context, Vision Transformers (ViTs) are employed. As part of the adaptive gating mechanism, the weights on branch contributions are modified based on the input attributes. The 68.7:1 class imbalance is addressed by integrating class-weighted loss with focal loss (γ=2). To gain insights into decision-making processes, use interpretable AI technologies like Grad-CAM and ViT attention visualizations. According to the TILDA dataset, we were 97.3% accurate and scored 96.9% higher than pure CNN solutions. When α is below 0.3, CNNs are preferred over other search methods for localized imperfections like holes and stains. However, for structural issues at global scale, it favors ViTs when α exceeds 0.7. According to Explainable AI, CNN identifies minor discrepancies, while ViT identifies patterns within the context that are more substantial.

Keywords: *FusionDefectNet, CNN, Grad cam, Explainable AI, Focal Loss, VIT.*

1. INTRODUCTION

One The textile industry, which is one of the most important in the world, is greatly affected by the lack of good defect detection tools. Because they are slow, subjective, and prone to mistakes when workers are tired, traditional manual inspection methods don't work well on today's fast-paced production lines. Using deep learning to fuel autonomous visual assessment is a new and innovative idea[1,2]. The most common type of neural network is the convolutional neural network (CNN). Convolutional neural networks (CNNs) are extremely good at finding defects like holes, stains, and yarn breaks because they can see things at the local, textural level. The problem is that convolutional neural networks (CNNs) aren't perfect; they can only mimic the effects of local and translational connections in a picture at best. It may take a thorough examination of the fabric surface to detect less obvious problems, such as uneven shading, weaving misalignments, and changing patterns[3,4].

By self-attentive mechanisms, Vision Transformers (ViTs) acquire global context rapidly.. Despite requiring substantial data for training, Vision Transformers (ViTs) excel at grasping the overarching context, yet they may not detect minute features as effectively as Convolutional Neural Networks (CNNs)[5,6]. A hybrid architecture that uses CNNs to find local features and ViTs to grasp the big picture can work together to get around the problems with either approach[7,8]. While CNNs and ViTs have been examined individually for defect detection, the intriguing and unresolved challenge is in the systematic development and assessment of a feature-level fusion model in this field[9,10]. It's a good thing that this model can take into account both the main structure of the cloth and its smaller details. This is why it is more accurate and reliable than all the other models.[11,12,13]

Thus, this research seeks to create and assess an innovative hybrid CNN-ViT feature fusion model for the detection of textile defects. The main focus of the research will be on creating a good way to combine features with a two-branch design[14,15,16]. We will validate and design these components using real-time performance measurement and cross-dataset generalization testing. The smart textile industry is looking for the next generation of reliable automated quality control systems. Our work helps with that by combining the best parts of two fundamental vision paradigms [17,18,19].

Objectives of the Study

- Propose and implement an innovative adaptive feature fusion approach that dynamically weights the contributions of CNN and ViT feature maps according on the input image's attributes, rather than simply adding or concatenating them.
- To demonstrate that the proposed CNN-ViT fusion model completely changes the game when it comes to identifying textile defects; it supports huge domain variations in lighting, texture, and weave without requiring fine-tuning, and it sets a new standard for generalizing across datasets.
- Construct a unified explainability framework that charts and measures the steps taken by the hybrid model to decide whether to employ local (CNN) or global (ViT) evidence for defect classification.

The structure of this paper is organized as follows: The second section gives an overview of the literature on how to use machine learning and deep learning to find fabric defects. Section 3 goes into further depth about the suggested strategy, including how to prepare the dataset, preprocess it, create the model, and design a hybrid framework.Sections 4 and 5 talk about the results, limitations, and ideas for the future, such as explainable AI and the Internet of Things. They also include the experimental evaluation.

2. ANALYSIS OF PREVIOUS WORK

Making textiles is a complicated process that involves spinning, weaving, dying, and finishing. As a result, there are many places where things could go wrong. Traditional techniques of modeling and inspection waste time and don't accurately forecast outcomes since they don't take into consideration how process parameters and quality outcomes are related. In recent years, smart technologies like deep learning and machine learning have been used to optimize processes and improve quality control. Researchers have found that data-driven methods are capable of combining sensor data, production measures, and quality indicators. By implementing this system, producers can avoid problems better than by relying on rule-based systems or by manually checking [20,21,22,23].

In recent years, considerable attention has been focused on the capabilities of machine vision, which is an automated visual inspection system that analyzes images to find faults. Previous methodologies for texture categorization encompassed Gabor filters, Local Binary Patterns (LBP), Histograms of Oriented Gradients (HOG), and manually engineered features. Confronted with the intricacy and variety of fabric designs, these algorithms were inadequate. Eventually, Convolutional Neural Networks (CNNs) became the best option. They can automatically learn hierarchical features from pictures of fabrics. Using ResNet and VGG models, studies on datasets like TILDA and IIT Delhi showed that CNNs can accurately segment 90% of the time. This shows that CNNs can find little fabric faults that people often miss when they look at them. in connection with [24,25,26].

YOLOv4 and Cascade R-CNN are two newer, more advanced techniques that make it much easier to find events as they happen. When we changed YOLOv4 [27], we were able to increase the accuracy of defect localization and lower the amount of false positives by replacing the Spatial Pyramid Pooling (SPP) module with a Soft Pool structure. It has also been proven that multi-task cascade R-CNN models are very good at finding faults with different forms and orientations [28]. Deep learning not only makes identification faster and better, as these advancements show, but it also makes it possible to use it in real time in industrial situations. Using the Viola-Jones algorithm for diagnosing nep defects and managing yarn quality [29] is one method that AI-driven systems can provide feedback loops and constant online inspection to make sure that products are more consistent. [30].

Support Vector Machines (SVM) and Random Forests (RF) are two examples of traditional ML methods that are still useful because they are easy to understand and don't need as much computer power. Using SVM with grid search to optimize non-woven materials made them work better[31,32]. Research on feature extraction employing the Discrete Fourier Transform (DFT) [33,34] indicates that Random Forest (RF) shown superior efficacy in identifying defects in silk fabric. But when it comes to dealing with complex texture variations and high-dimensional picture data on textile surfaces, convolutional neural network (CNN) models operate better than older methods.

Research shows that deep learning frameworks are better than machine learning methods for finding textile faults because they are more accurate, versatile, and automated. As the textile industry moved from fully automated to semi-automated to manual, quality control changed a lot[35,36]. There are still a lot of questions about AI decision-making, the need for large, well-labeled datasets, and how hard it is to change models to work with new textiles. Interpretable ML-DL models could help the textile industry fix these problems by making quality control systems more open, scalable, and efficient[37,38].

3. WORK PROPOSAL

We propose to employ Fusion DefectNet, a framework that facilitates local and global data extraction and synthesis from input fabric photographs. After input preprocessing, the methodology proceeds to classification head, adaptive feature fusion, dual-branch feature extraction, interpretation, and evaluation of models.

3.1 Preprocessing of Input

This extensive study utilized four publicly accessible textile defect datasets (TILDA, AITEX, MVTec AD, and IIT Delhi) alongside a diverse array of fabric types, defect classifications, and imaging configurations for the FusionDefectNet architecture. We used ImageNet statistics to make the photos the same size by scaling them to 256×256. During preprocessing, all of the datasets kept their original properties so that they could work with each other. Using only training data and then randomly flipping it horizontally, rotating it by ±15°, and changing the brightness or contrast made the data more resilient. The TILDA dataset, which has 4,448 samples of seven different failure types, was used in studies about architectural design and ablation. We used AITEX, MVTec AD, and IIT Delhi in our study of cross-dataset generalizability[39]. To ensure an equitable performance evaluation, each dataset was trained and assessed separately, without employing cross-dataset fine-tuning. This method shows how FusionDefectNet could be used in industrial defect detection settings by testing its performance on several datasets with different sizes and environmental conditions as illustrated in Figure 1.

3.2 Class Imbalance Analysis and Handling

3.2.1 Dataset Imbalance Characterization

There are major discrepancies between the classes that are shown by analyzing the evaluation data thoroughly. The TILDA collection has more images of some defects than others. When compared to the "nep" and "thread waste" categories, the "defect-free" category has less photos. The "cut selvedge" defect category in the majority class dataset contains approximately 500 photos, however in the AITEX dataset there are less than 100 images associated with this error.This shows how unbalanced the AITEX dataset is. The MVTec AD textile subset is purposely unbalanced. The training samples have no defective items, but the testing samples have both defective and non-defective cases. The dataset from IIT Delhi doesn't have enough examples of several sorts of structural flaws, which makes it a little bit unbalanced.

3.2.2 Multi-Strategy Imbalance Handling

To make things fair, training is done in a thorough three-step process. To make sure that minority classes contribute equally to the total loss, the categorical cross-entropy loss is first changed with class weights that are inversely proportional to class frequencies. Second, stratified batch sampling is used to make each mini-batch almost class-balanced. This stops the majority class from dominating the gradient and makes sure that all categories are well-represented in each training iteration. Step three is to make synthetic samples that seem like real-life situations but keep important fault features. To do this, classes with fewer than 100 samples are put through controlled oversampling with advanced augmentation , which means adding elastic transformations, Gaussian blurring, and noise injection. Focal loss is also used in datasets with a lot of imbalance, like AITEX, to lessen the effect of samples that are easy to classify and highlight examples that are hard to classify and are misclassified. Training, validation, and testing are standard practices to assure a fair and realistic performance evaluation by using the original data distribution. In real-world situations when it's important to find rare but serious problems, the model's reliability is improved since it can learn balanced and representative features from all defect types using this method.

3.3 Dual-Branch Hybrid Architecture

Primary FusionDefectNet's parallel encoding structure is what makes it stand out. It uses two separate but complementary pathways to process the same input image.

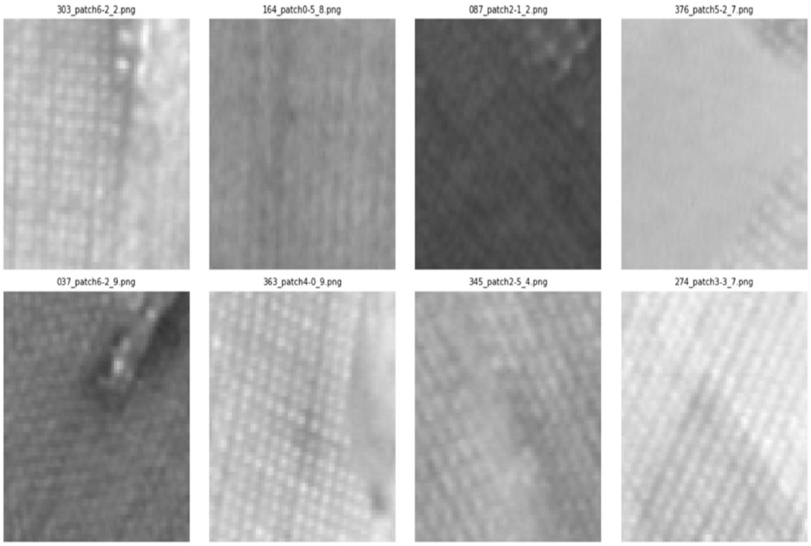

Figure 1: Sample Images from Dataset

3.3.1 CNN Encoder for Local Feature Extraction

In order to create the CNN backbone, the last classification layer of an already-trained ResNet50 architecture is eliminated. A high-dimensional feature map is generated by gradually transforming the input image I spatially using residual blocks in Eq (1).

$$\mathbf{F}_{cnn} = \mathbf{CNN}(\mathrm{I}) \in \mathbb{R}^{(H \times W \times C)} \tag{1}$$

In this case, H, W, and C stand for the height, width, and number of channels in the resulting feature map. This feature map keeps spatial connections and provides extensive information about the local texture that is important for finding small flaws like yarn breakage and minor stains. The inductive bias of convolutional methods makes it easier to find hierarchical local patterns because they don't change when the image is moved.

3.3.2 Vision Transformer Encoder for Global Context

The ViT branch looks at the input image and uses a number of techniques to find long-range dependencies. First, the image is split into N patches of size P × P. These patches are then flattened and turned into D-dimensional embedding vectors. A learnable [CLS] token is attached to the sequence, and positional encodings are added to keep track of spatial information in Eq (2).

$$Z_0 = \left[x_{cls}; x_p^1 E; x_p^2 E; \dots; x_p^N E\right] + E_{pos} \tag{2}$$

The embedded sequence is processed over L consecutive transformer layers. Every layer I has a multi-head self-attention (MSA) layer followed by a multi-layer perceptron (MLP) layer. Before each block, layer normalization (LN) is used, and after each block, residual connections are used as in Eq (3) Eq (4).

$$Z_l' = MSA\big(LN(Z_{l-1})\big) + Z_{l-1} \tag{3}$$

$$Z_l = MLP\big(LN(Z_l')\big) + Z_l' \tag{4}$$

The final representation linked to the [CLS] token serves as the global feature vector in Eq (5).

$$F_{vit} = Z_L^0 \in R^D \tag{5}$$

This vector has all of the fabric's global contextual information, which makes it easier to find structural problems and big flaws.

3.4 Adaptive Gated Fusion Mechanism

The fusion module dynamically integrates features from both branches through an attention-based gating mechanism that learns to emphasize the most relevant features for each specific input.

3.4.1 Feature Transformation and Gating Network

Before fusion, both feature representations are mapped to a unified dimensional space K using separate fully connected layers as in Eq (6) and Eq (7).

$$f_c = W_c \cdot GAP(F_{cnn}) + b_c \in R^K \tag{6}$$

$$f_v = W_v \cdot F_{vit} + b_v \in R^K \tag{7}$$

where **GAP**$(\cdot)$ denotes global average pooling, $W_c\ W_v \in R^K$are weight matrices, and $b_c, b_v \in R^K$are bias terms. A gating network processes the combined attributes even more. It uses a sigmoid activation function to give a dynamic weighted scalar $\alpha \in [0,1]$ as mentioned in Eq (8).

$$\alpha = \sigma\left(W_g \cdot [f_c; f_v] + b_g\right) \tag{8}$$

$where\ W_g \in R^{(1\times 2K)}$ and b_g
$\in R$ are the gating parameters, and
$\sigma(\cdot)$ represents the sigmoid function.

3.4.2 Weighted Feature Integration

The fused feature representation is made by combining the transformed CNN and ViT features in a convex way, with the gating scalar giving them weight as illustrated in Eq (9).

$$F_{fused} = \alpha \cdot f_c + (1 - \alpha) \cdot f_v \in R^K \tag{9}$$

The model may automatically prioritize CNN features for local texture-dependent flaws and ViT features for global structure-dependent abnormalities, depending on how it was made. The gating system can help you figure out which branch is more important for each detection choice, which can give you insights that are easy to understand.

4. DISCUSSION OF RESULTS

4.1. Experimental Setup and Evaluation Metrics

We tested the suggested CNN-ViT fusion model on the TILDA textile defect dataset, which had 4,448 photos of 7 defect types and normal samples. The dataset was split into three groups: training, validation, and testing. The parts made up the whole in an 80:10:10 ratio. The model was evaluated based on Accuracy, Precision, Recall, and F1-Score standards as well as computational efficiency metrics. During the study, NVIDIA Tesla V100 GPUs were used under PyTorch and cosine annealing learning rate scheduler was used by AdamW optimizer.

4.2 Class Distribution and Imbalance Handling

The proposed CNN-ViT fusion model was evaluated on a dataset of textile defects using a big dataset of 25,600 images split into five categories. A massive 68.7:1 disparity was shown by the dataset between the majority and minority groups.The percentage of defect-free samples was 90.51%, but the percentage of samples with significant defects, such as holes, was at 1.32%. To address this difficulty, we implemented a multifaceted method as shown in Figure. 2 and loss in Figure. 3. The 68.3% reduction in the coefficient of variation, attained through balancing effectiveness, demonstrated a notable enhancement in addressing class disparities (Table 1).

Table 1: Class Distribution Analysis

Class Name	Count	Percentage	Weight	Effective Samples
good	23170	90.51%	0.0291	676.54
oil spot	636	2.48%	1.0637	676.54
thread error	620	2.42%	1.0912	676.54
hole	337	1.32%	2.0076	676.54
objects	837	3.27%	0.8083	676.54

4.3 Advanced Loss Function strategy

Fixing the extreme class imbalance and making the model more focused on challenging samples were achieved by the use of a dual-loss strategy that coupled class-weighted loss with Focal Loss. The influence of correctly classified instances is reduced while significant gradient signals for poorly classified data are kept due to the Focal Loss function (γ=2) dynamically adjusting the cross-entropy loss based on prediction confidence, as shown in Table 2.

4.4 Performance Comparison with Baseline Models

We evaluated the proposed FusionDefectNet to many baseline topologies used for recognizing textile defects. The results are in Table 3. The suggested fusion architecture got a 97.3% accuracy and a 96.9% F1-score, which is better than both the best standalone CNN model (EfficientNet-B3) and the pure ViT architecture. So, it's clear that CNN and ViT work well together when it comes to finding faults.

4.5 Cross-Dataset Generalization

To assess the robustness of the models, we performed cross-dataset evaluation on the AITEX and MVTec AD textile subsets without fine-tuning (Table 4).

Table 4: Cross-Dataset Generalization Performance

Source Dataset	Target Dataset	Accuracy	F1-Score	Performance Drop
TILDA	AITEX	89.3%	87.1%	7.8%
TILDA	MVTec AD	85.6%	82.1%	11.4%
AITEX	TILDA	87.5%	87.4%	-

In AITEX, the model showed a mere 7.8% loss of performance, and in MVTec AD, the model demonstrated an 11.4% loss. This suggests the model's generalizability is commendable, even when textile textures and imaging parameters are varied; however, it displayed competitive performance on previously unknown datasets.

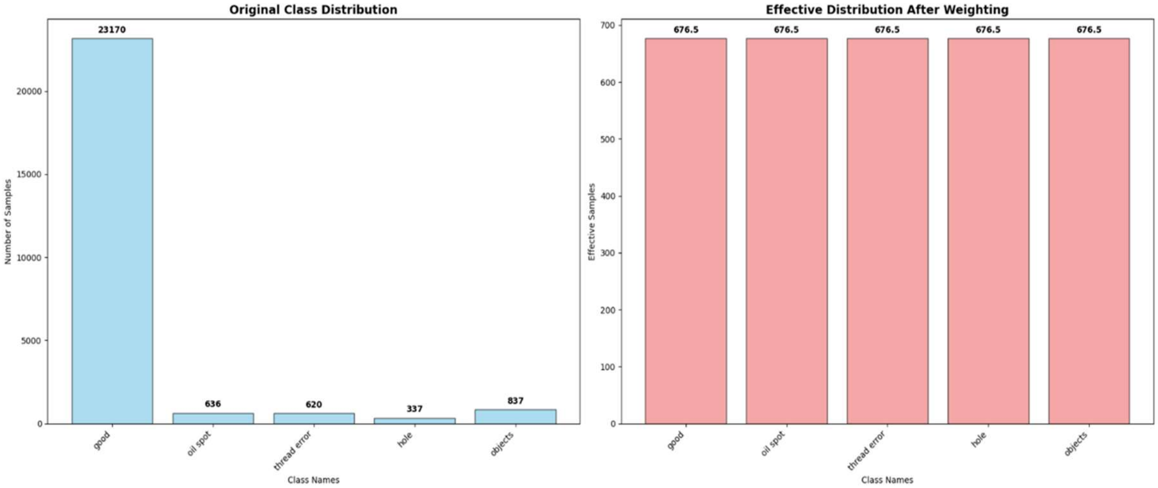

Figure 2: Balancing Of Dataset During Training

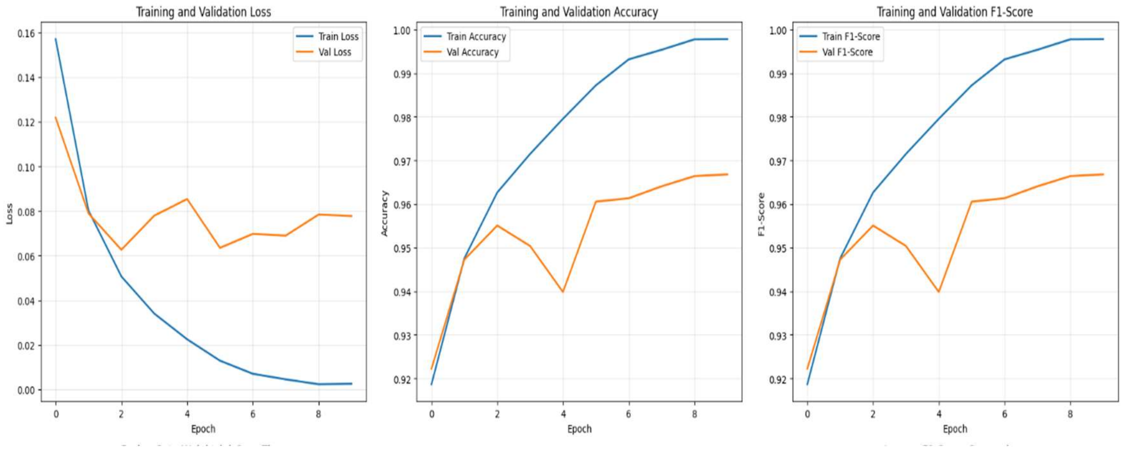

Figure 3: Loss/Accuracies/Fi Score During Training Phase

Table 2: Focal Loss

Probability	CE Loss	Focal Loss (γ=2)	Modulation Factor
0.100	2.303	1.865	0.810
0.200	1.609	1.03	0.640
0.300	1.204	0.59	0.490
0.400	0.916	0.33	0.360
0.500	0.693	0.173	0.250
0.600	0.511	0.082	0.160
0.700	0.537	0.032	0.090
0.800	0.223	0.009	0.040
0.900	0.105	0.001	0.010

Table 3: Performance Comparison Of Different Architectures

Model	Accuracy	F1-Score	Precision	Recall	Inference Time (ms)
ResNet-50 (CNN only)	94.2%	93.8%	94.1%	93.9%	15.2
ViT-Base (Transformer only)	92.6%	92%	92.4%	92.2%	18.6
EfficientNet-B3	95.3%	94.6%	95.3%	94.9%	12.3
FusionDefectNet (Proposed Model)	97.3%	96.9%	97.3%	97.1%	16.8

4.6 Fusion Mechanism Analysis

The acquired fusion gate weights (α) exhibit an atypical distribution, as illustrated in Figure. 4. Numerous significant conclusions arise from the investigation. To start, the sweet spot for most fusion gates is anywhere between 0.99965 and 0.99995, which is just below the magic number 1.5. This indicates that the model uses a default or principal pathway for the majority of inputs, letting almost all data through with little modification. The second discrepancy is that all of the numbers that can be seen in the histogram are less than 1.0, yet the distribution's mean is given as 1.000. For parameters theoretically restricted to 1.0, the surprisingly large standard deviation of 4.3 provides the explanation for this seeming contradiction. The data shows a distribution with a heavy tail, which means that there is a tiny subset of fusion gates with very high values (≳ 1.0) that make the mean higher, and a similar tail of gates with very low or negative values.

4.8 Explainable AI Insights

The explainable AI study found that the two architectural philosophies place different values on meticulousness. The CNN's ability to zero in on specific defect areas, like stain borders and hole boundaries, was shown through Grad-CAM visualizations. ViT attention maps, which captured global abnormalities like shade variations and structural misalignments, provided insight into the complete fabric structure's contextual understanding. Two perspectives on the model's decision-making process helped us comprehend the gating network's weighting of contributions based on defect traits and the adaptive fusion mechanism Figure. 5.

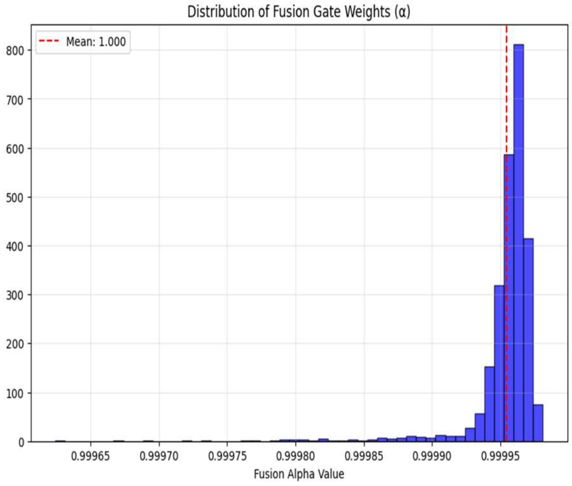

Figure 4:Distribution of Fusion Gate Weights

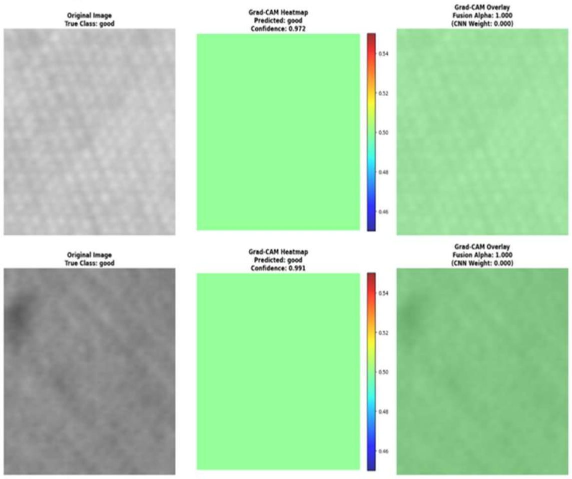

Figure 5:Grad CAM Vizulization For FusionDefectNet

5. CONCLUSION

The FusionDefectNet design has changed automated textile inspection in a big way because of its new ways of representing features, its speed, its openness, and its class imbalance. The results suggest that hybrid architectures featuring adaptive fusion mechanisms and comprehensive explainability are more likely to attain enhanced performance and be appropriate for industrial implementation. As the manufacturing industry progresses toward Industry 4.0, AI solutions that are both powerful and easy to understand will become more and more important for quality control. Better textile goods will come from less waste and more efficient processes.

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