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Fabric Quality Assurance System: Defect Detection and Image Reconstruction using Gen AI

Ananya Doshi*[1], Vansh Dodiya[2], Hetansh Shah[3], Kranti Ghag[4], Nilesh Patil[5], Meera Narvekar[6]

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Abstract: Textile waste comprises of one of the largest categories of waste produced, both in India and worldwide. Determining the quality of fabrics and discarding the damaged ones at an initial stage during mass production is essential to maintain a standard of optimal quality. Additionally, it is vital to consider the efficiency of existing systems a parameter to determine the performance of defect detection process. This paper aims to address the importance of robust textile defect detection by proposing one of the best performing anomaly detection algorithms to implement binary classification and a customized Convolutional Neural Network (CNN) to implement multiclass classification. In addition to this, the concept of Generative Artificial Intelligence (GenAI) was also incorporated where new images were reconstructed using autoencoders and then predicted based on the concept of Kernel Density Estimation (KDE). Binary and multiclass classification were performed on two datasets, where one was obtained from Kaggle and another was custom made. Image reconstruction was performed only on the dataset obtained from Kaggle. The performance of these algorithms implemented and proposed was analyzed based on various evaluation metrics.

Keywords: *autoencoders, Convolutional Neural Network, Generative Artificial Intelligence, Kernel Density Estimation.*

1. Introduction

Many countries face huge challenges with textile waste so industry experts are looking for better ways to reduce waste and increase production efficiency. More than 92 million tonnes of textile waste is generated worldwide and it is predicted that this figure will go past 130 million tonnes by 2030, if appropriate steps are not taken to reduce waste globally. It is estimated that over one million tonnes of textile waste is generated annually in India, making it the third largest urban solid waste in the country.

This research seeks to identify the faults of mass production of garments in the textile industry. The main objective is to eliminate damaged garments before they are exported or shipped to suppliers, increasing the overall standard. During the process of manufacturing fabrics, various issues such as knots, metal fouling, holes, other imperfections arise in fabrics, which need to be identified for quality assurance. If we ever just classify fabrics as good or damaged besides, this project will use a multi-dimensional classification. Users will interact with the application to provide high-resolution images captured by the camera for testing.

These images will then be processed by machine learning algorithms that will generate high-quality reports detailing each detected fabric defect. In our approach, multiple machine learning models with multiple architectures and hyperparameters can be developed to ensure efficient performance. In addition, we aim to find ways to reuse worn out textile parts through Generative Artificial Intelligence (AI) and incorporate them into existing textiles, thereby reducing waste and enhance sustainability in the textile industry. This model plays a specific role in improving garment quality, especially in mass production situations.

To ensure that the customers receive high-quality fabrics, it is significant to find anomalies in the heavily produced textiles. Efficient quality control subsides waste and production costs while simultaneously improving consumer satisfaction. Manufacturers can increase operational efficiency and save expenses related to rejection and replacement by promptly recognizing textile defects and stopping faulty products from reaching the end-users. When compared to conventional visual inspection procedures, automatic defect detection methods which use deep learning models put forward enhanced speed, accuracy, and efficiency while streamlining the production process. The present research undertakes a thorough examination of diverse diagnostic methodologies for fabric issues, pinpointing the optimal procedures for scenarios including binary and multiclass classification. Additionally, it tackles the drawbacks of current methods, highlighting the need for improvements in fabric defect diagnostics by addressing issues including their dependence on a single metric

[1] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0009-0002-9643-6038
[2] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0009-0004-9798-6730
[3] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0009-0004-0768-8378
[4] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0000-0002-4961-1633
[5] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0000-0001-8335-4426
[6] *Dwarkadas J. Sanghvi College of Engineering, India*
ORCID ID : 0000-0003-4602-4094
* *Corresponding Author Email: doshiananya2002@gmail.com*

accuracy and susceptibility to modifications in input pictures. The study also looks at possible approaches for improving accuracy and precision, showing areas that could use more research and development.

2. Literature Survey

[1] utilizes CNN, Single Short Detection (SSD) and MobileNetV1 architecture for the detection of fabric anomalies, where an accuracy of 97% was achieved. However, this research only used a single metric, that is accuracy to check model's performance. In the proposed solution of this project, various evaluation metrics like precision, recall, f1-score, loss function and errors were utilized to analyse results, thereby providing a robust measure of result evaluation. Additionally [2] has performed classification of defects using Squeeze and Estimation (SE) module based YOLOv5 where SE-YOLOv5 achieved an accuracy of 95.52%. But this approach only evaluated the results for variations of YOLO and not for different transfer learning models. In our research, ResNet50 quantifier was implemented for various anomaly detection models after the slight poor performance showed by InceptionV3, suggesting scope for significant improvement. Also, our proposed solution involves reconstruction of new images through autoencoders on a custom dataset where images of genuine clothes were captured through the macro lens of camera. On the other hand, [3] used unsupervised UNet and Generative Adversarial Networks (GANS) to generate new images but no data with real defects was considered as all the defect data was artificially created. In [4], a two-stage framework for fabric defect detection was created where R-Net was a reconstruction network and U-Net was a decision network. But the major gap encountered was that the model was only trained with defect free images. In our methodology, we trained all algorithms on both, good as well as good and bad images, and noticed a considerable performance improvement while training with defect and defect free images combined. Various models like MPANet, CenterNet, YOLO X and RCNN were used in [5] for extracting features and then trained for classifying defects where it was observed that MPANet produced the highest accuracy of 92.6%. However, the major limitation of this study was that the system required high computational time, making the system infeasible for industrial usage. To reduce the time required for training models on such large datasets, we have employed various regularization techniques, batch processing and parallel feature extraction to improve speed.

Though the research proposed in [6] provided an accuracy of 98.15% using the Improved Dragonfly Optimization (IDFODL-FDC) technique, the dataset used for experimentation had extremely less data with only 56 samples. To make a system reliable and diversely applicable, the dataset which we have utilized in our research contains massive amount of diversely annotated data, thereby making the system more efficient. Another system proposed in [7] implemented Alternating direction method of multipliers and weighted double-low-rank decomposition method (WDLRD) for defect detection where a guide prior map was generated to assist the detection and solve the optimization problem. However, this research is limited to determining whether the fabric is defective or not. It does not perform well for fabric with different and varied textures and patterns. This issue has been addressed in our proposed research where the models are capable of determining which category of defect is present, thereby accurately identifying fabrics with varied textures and patterns. Furthermore, the system proposed in [8] where anomalies were detected using Faster RCNN was effective only for smaller sized defects. Here, Deep residual network was used for feature extraction and multi-scale fusion was used for small defect detection. The system proposed in our research does not only identify small defects, but also identifies large defects accurately. This is due to the availability of diversely annotated dataset for training the models, thereby making the system efficient enough to capture all sized defects. In [9], CNN and VGG16 were combined together to make multipath neural network with Gabor filter to classify defects where an accuracy of 97.5% was achieved, obtaining a difference of nearly 0.007 for two different datasets. However, a large amount of time was required while training the models, resulting in high computational costs. Also, The dataset used in [10] also contained a drastically low number of images with only a total of 165 images. A hybrid of CNN and Variational Autoencoder (VAE) was created where the model achieved an accuracy of 86% for box patterned fabric and 98% for dotted pattern. Our proposed solution utilized an extremely large dataset for training, classifying a large category of defects, not just limited to two types of patterns. Moreover, a highest accuracy of 100% for hole pattern was obtained while considering the custom dataset for training.

In [11], Improved GAN and implicit rank minimization auto-encoder is used to reconstruct images with no defects from the images with defects. Thus, the system will not accurately detect defect in larger images. The proposed solution in this paper uses defect as well defect free images for model training and thus ensuring the categorical detection. Additionally, the system proposed in [12] uses TILDA texture dataset and implements VGG19 algorithm, where it achieved an accuracy of 94.65%. But the drawback is that it only implements a single model for obtaining the result. The system proposed in this paper implements multiple algorithms and compares the performance of each of them. [13] proposes research which implements single classification SVM with polynomial kernel for training reaching 96.4% accuracy of classification. This system uses a dataset of non-woven fabric which is not feasible during mass production of fabric. Therefore, a well-designed and knitted fabric dataset must be used. The proposed method in [14] uses AMTFNet with attention mechanism to focus on defects and multitask fusion to improve classification. It has achieved a precision of 98% score, 99.4% recall score and 98.7% f1 score. But it is only limited to detect the normal samples and fails to address the unsupervised anomaly detection task. Our proposed solution in this paper classifies both the defective and normal class and also provides accurate results on unseen data. Also, the solution provided in [15] proposes a technique using adaptive canny operator and single scale Retinex approach and achieved an accuracy of 97%. This technique worked well on knitted fabric but failed if there were wrinkles present on the fabric. Wrinkles are a crucial factor of consideration and therefore our proposed solution contains custom made dataset which contains images that have wrinkles along with the categorical feature that image represents.

In [16], VGG16 autoencoder is used to reconstruct images Structural similarity index (SSIM) to determine defected region. With SSIM threshold set to 0.5 an accuracy of 99% was achieved. Since this autoencoder is highly complex in nature it required high computation time and cannot be used for real time detection. This is overcome by the proposed solution in this paper as it can detect defects in quicker way. The proposed solution in [17], Mask R-CNN is used to detect the defect in fabric. It achieved and accuracy of 83.5% but is limited only to detect the defective image and not identify the category of the defect. One of the methods presented in this paper is multiclass classification which provides category of the defect. Another system proposed in [18], uses Median filtering and logarithmic enhancement, FT algorithm and projection method, SLIC super pixel segmentation and binarization. The dataset used in this approach had limited number of labelled samples and background textures caused misclassification of various images. Thus, it is important to have a robust and correctly labelled dataset. The comparison of two datasets is shown in this paper. The solution presented in [19] uses RDUNet-A to perform segmentation which is based om autoencoders. It achieved pixel accuracy of 60% which can be improved further. But the system is incapable of segmenting flaws in dense pixels and real time segmentation is not possible. This technique can be improved further and pixel accuracy can be increased as during real time detection the accuracy must be significant enough to not produce false classifications. Also, [20] proposes a system with New optimal Gabor wavelet algorithm, Defect Direction Projection Algorithm (DDPA). The DDPA achieved an accuracy of 96.97% and is considerably fast in detecting the defect. The dataset used in this approach had images which provided resistance to lighting and texture of the dataset. The proposed solution in the paper has perfectly annotated datasets, which makes the results more reliable and accurate.

3. Methods

The proposed solution about this research has been explained in detail in the below section. The section discusses various algorithms that have been implemented for performing the binary classification of defects, multiclass classification of defects and generation of new patterns and data augmentation through generative AI models.

The dataset which was initially in HDF5 format was converted to images. These images were then respectively stored in training and testing directories. During training data generation, data augmentation was performed on good images using methods like horizontal and vertical flipping to reduce the imbalance of data, which earlier was 20% good images and 80% damaged images and later turned out to be 44% good images and 56% damaged images.

3.1. Binary Classification:

The term Binary classification determines basically whether the fabric is containing anomaly or not. This phase is crucial and is generally employed during the initial phase of defect detection during mass production of fabrics. Before proceeding with the binary classification on the data, exploration and preprocessing of data was done to gain a better understand the data so that models could be selected accordingly.

To proceed with binary classification, a 'quantify_image' function was created that took images as an input, converted them to HSV color shape, normalized them and then reshaped the images to default size 229*229*3. The pre-trained InceptionV3 model was thus used to extract the features. The features extracted were then returned as a 1D numpy array of size 1000, indicating 1000 classes of InceptionV3 quantifier. Utilizing this quantifier, several models were implemented to perform binary classification which are discussed in detail below.

3.1.1. Isolation Forest:

Isolation Forest is one of the widely used unsupervised machine learning algorithms for anomaly detection. It is an ensemble method which calculates the average of predictions of various decision trees in order to assign anomaly score to any data. Instead of determining and classifying a particular fabric as normal and then categorizing the rest as anomalies, it learns to isolate a damaged portion of fabric from a set of images. For better performance, the model was passed with hyperparameters 100 trees, 0.1 contamination rate and 42 random seed. After training the model using the above-mentioned quantifier, an image was loaded whose features were extracted and the trained model displayed it as good or damaged. Additionally, if the image was anomalous, the region of defect was also located along with the label by plotting a bounding box.

3.1.2. Elliptic Envelope:

The next model which was implemented was Elliptic envelope, which is also an unsupervised machine learning technique in anomaly detection. Elliptic Envelope was trained next since it is more robust to outliers than Isolation Forest and gives better results for data that follow gaussian distribution, specifically when anomalies are quite distinct from normal images. While implementing this, a high support parameter of 0.9 was chosen, indicating the inliers in support, so that a complex model could be created, capable of capturing variability in data. Additionally, contamination of 0.1 and random state of 42 was chosen. Results were then analyzed by loading a random image from test data.

3.1.3. Local Outlier Factor (LOF):

The LOF algorithm was implemented next, which is also a commonly used unsupervised anomaly detection technique. It is responsible for calculating local density deviation of data with respect to its neighbour and assigning anomaly score on the basis of how isolated a data point from its neighbour. Outliers are those samples which have density lesser than their neighbours. The parameter n_neighbour is generally set greater than minimum number of samples contained within cluster. While implementing binary classification on textile data, n_neighbours was set to 20. Lastly, a random test image was loaded and prediction was made based on the trained model.

3.1.4. One-Class SVM Model:

Next, one-class Support Vector Machine (SVM) model, was trained. This model was chosen specifically for its ability to identify anomalies by learning the normal images and then classifying all the images that are not similar to the learned data as damaged ones. This algorithm can effectively capture complex decision boundaries in high dimensional datasets. Similarly, after training this model, a sample image was loaded from test data result was obtained along with labels and bounding box around the damaged portion of fabric.

3.1.5. SGD One-Class SVM Model:

Stochastic Gradient Descent One-Class SVM was preferably implemented next after traditional one class SVM because it offers faster training and reduced computational load while working with large datasets. This is because SGD incrementally updates the model parameters based on mini-batches of data, rather than processing data in every iteration, reducing memory requirements and computational costs. It provides more generalization and can efficiently reduce noise as compared to traditional one class SVM. A pipeline was also created consisting of Nystroem kernel approximation followed by an SGD One-Class SVM model to improve the overall scalability. After training, prediction was made by loading a test image. The result was displayed with the appropriate label and bounding box around the damaged portion of fabric.

In order to improve the overall accuracy of binary classification, models trained above, the pre-trained ResNet50 quantifier was created next. This quantifier provides more different feature representations as compared to InceptionV3 model, due to presence of dense layers and skip connections. This distinct feature capturing ability provided optimal results for detecting good and damaged portions of the fabric. All the models listed above were then implemented next, using ResNet50 as a quantifier and feature extractor. Significant result improvement was observed.

3.2. Multiclass Classification:

Binary classification is just limited to defining whether a fabric is containing a defect or not. However, in order to investigate the depth of anomaly, multiclass classification steps in. This part of the research has not only classified the image into good and damaged, but also further classified which kind of damage has been present. The image is here stored into 6 classes in their respective train and test directories. The six classes are good, color, cut, hole, metal_contamination and thread.

There are 72000 images present in train directory and 36000 images present in the test directory, hence the train test split ratio is 3:1. Additionally, there is no class imbalance observed while exploring the data, each class comprises approximately 17% of the images.

To implement multiclass classification, a customized Convolution Neural Network (CNN) was created from scratch. CNNs are one of the most popular computer vision techniques that hold wide variety of anomaly detection applications. The CNN which was created here contained 8 layers. A series of convolution layers and max pooling layers were stacked together linearly and the increasing number of filter and kernel sizes make it more efficient to capture the features from input data. A global average max pooling layer was stacked at the end of network to reduce noise and spatial dimensions, favouring a more robust learning experience. This was followed by a number of dense fully connected layers and output layer with softmax activation function for multiclass classification.

The two callbacks defined while creating the model were ReduceLROnPlateau and EarlyStopping. ReduceLROnPlateau callback reduces learning rate if model's val_loss doesn't improve for 1 epoch. The learning rate was chosen as 0.0000001. EarlyStopping stops training if the validation loss does not improve for a certain number of epochs to prevent overfitting. Here the patience parameter was declared 3, which means that training would stop if validation loss does not improve for 3 consecutive epochs, thereby generalizing the model better.

The model was compiled using categorical cross-entropy loss (suitable for multiclass classification), the Adam optimizer, and accuracy as the evaluation metric. The categorical cross-entropy loss was calculated using following equation:

$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \tag{1}$$

$$CE = -\sum_i^C t_i \log(f(s)_i) \tag{2}$$

In the specific (and usual) case of multiclass classification the labels are one-hot, so only the positive class C_p keeps its term in the loss. There is only one element of the Target vector t which is not zero t_i=t_p. So discarding the elements of the summation which are zero due to target labels, we can write:

$$CE = -\log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right) \tag{3}$$

After training, the model's performance was evaluated on the test dataset. Finally, a classification report was printed, indicating metrics like precision, recall, and F1-score for each class.

3.3. Generative Artificial Intelligence:

Generative Artificial Intelligence (GenAI) is an increasingly growing field nowadays finding variety of applications in computer vision domain. The concept of GenAI has been employed in this research with the main aim of reconstructing new images from original ones, thereby fostering data augmentation. As we know, massive amount of data is required for training in order to achieve satisfactory results. This system can be used before the stage of identifying the defects by feeding a greater number of images reconstructed from original data so that model learns the features better.

Autoencoders, unsupervised learning models have been implemented here to reconstruct input data. During training, the encoder, containing convolution and maxpooling layers extract the meaningful features from input data. The decoder, which is stacked with convolutional and upsampling layers reconstructs new patterns from learned latent space feature representation. Relu activation was used in both encoder and decoder to provide non linearity and the models were compiled separately with the Adam optimizer and Mean Squared Error (MSE) loss function. The full autoencoder model was then created by combining the encoder and decoder models using Sequential API and compiled using Adam optimizer and Mean Squared Error (MSE) loss function. The formula for Mean Squared Error (MSE) reconstruction error is:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{4}$$

Where:

- N is the total number of pixels in the image.
- x_i is the i^{th} pixel value of the original image.
- $\hat{x}_i$ is the i^{th} pixel value of the reconstructed image.

Reconstructed images can provide insights into the appearance of defects by highlighting areas of deviation from the normal fabric pattern. This can aid inspectors or quality control personnel in identifying and categorizing defects more accurately.

The encoded output of input images obtained using the encoder were flattened. This is done to prepare the data for fitting the Kernel Density Estimation (KDE) model.

Next, the estimated probability density and reconstruction error (Mean Squared Error (MSE)) were calculated for both good (uninfected) and anomaly (defective) images. The formula for reconstruction error can be found above and to find out the estimated density is mentioned in below equation.

The formula for Kernel Density Estimation is:

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) \tag{5}$$

Where:

- $\hat{f}(x)$ is the estimated probability density function.
- n is the number of samples.
- K_h is the kernel function with bandwidth h.
- x_i are the sample points.

The density indicates how likely it is for an image to belong to a particular distribution in the latent space and the reconstruction error quantifies how well the autoencoder is able to reconstruct the input images from their encoded representations. If the reconstruction error is high, it indicates an anomaly or deviation from the normal patterns learned during training.

A reconstructed image was then loaded and the calculated density and reconstruction error were compared with predefined thresholds. Based on the thresholds, it was determined whether the image is classified as an anomaly (defective) or not. If calculated density was less than predetermined density threshold, the image was classified as an anomaly, else not.

4. Results and discussion

The above-mentioned methods were implemented and the results of each of them will be discussed in the following section. The binary classification and multiclass classification have been performed on two different datasets. The first dataset by MVTec for Anomaly Detection is used. The dataset contains 108000 images combined in the following 6 classes: good, color, cut, hole, metal contamination and thread. Among these 6 classes, except the good class, the rest of them are defective or damaged classes. The 5 defective classes are combined together as a damaged class for binary classification and separately for multiclass classification. The second dataset is custom-made by the coauthors with 2280 images belonging to the above 6 classes. This dataset is created through the macro lens of the Oneplus Nord smartphone with a 2 MP sensor with f/2.4-aperture lens. The macro lens helps in clicking highly pixelated images of the fabric for accuracy and precision. The metrics used for performance evaluation were precision, recall, and f1-score.

To perform the binary classification, the above five algorithms were implemented with both Resnet and Inceptionv3 quantifiers and they provided the following accuracies on MVTec AD and custom-created dataset. In almost every algorithm for both the datasets, Resnet quantifier performed better, gaining higher precision. Fig. 1 provides a comparative analysis of precision achieved by the five algorithms for InceptionV3 and Resnet quantifier. Similarly, Fig. 2 represents the same for the custom-created dataset. The Elliptic envelope algorithm achieved a precision of 82% which is the highest among all the algorithms in the MVTec AD dataset, through the Resnet quantifier. For the custom-created dataset the highest precision achieved was by Elliptic envelope for Resnet with 57% precision.

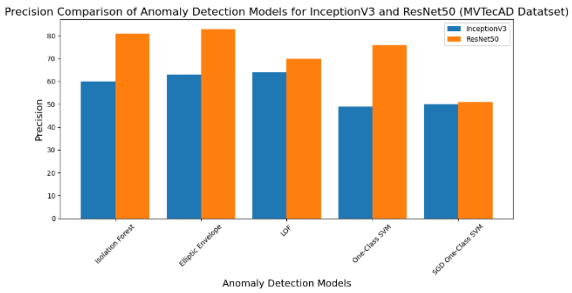

Fig. 1. Precision comparison for MVTec AD dataset

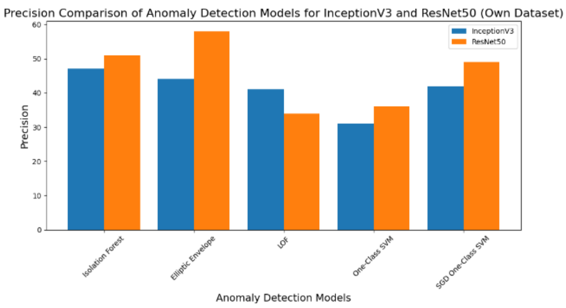

Fig. 2. Precision comparison for custom dataset

Along with the binary classification, it can also detect the region of the defect by creating a box around it. The Fig. 3 not only displays the image as an anomaly but also highlights the region of anomaly precisely. Through the usage of this region detection the location can be accessed while the fabric is manufactured in the industries.

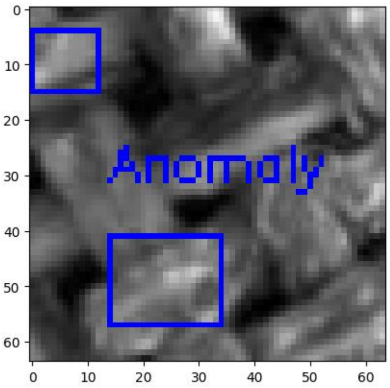

Fig. 3. Fabric sample with defect

Table 1 Class Number and Class Name used

Class Number	Class Name
0	Good
1	Colour
2	Cut
3	Hole
4	Metal
5	Thread

CNN was implemented for the multiclass classification for detecting the type of defects. Considering the MVTec AD dataset, the precision for individual classes is displayed below, with metal contamination receiving the highest precision amongst all classes. It can be inferred from Fig. 4 that the customized CNN algorithm is proficient for only certain types of defects in the dataset. Thes same is done for the customized dataset and below are the achieved precision for each of the classes. The system acquired 100% precision for hole and metal contamination classes. Multiclass classification for the MVTec AD dataset reached a precision of 80% for the metal contamination defect.

Among the two datasets, the customised dataset has performed better than the MVTec AD dataset as the Fig. 4 displays the comparative analysis.

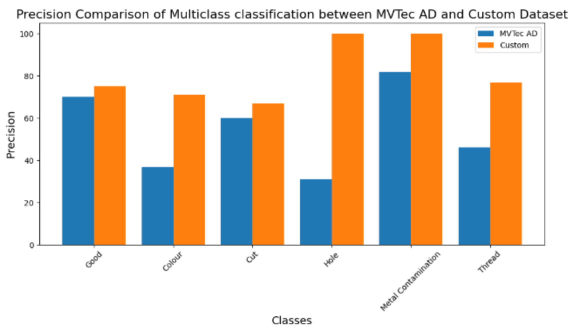

Fig. 4. Comparative analysis for both datasets

The usage of generative AI in the fabric industry is a unique approach to develop an idea that can upgrade itself continuously. Autoencoders are used for the implementation of generative AI models that can produce reconstructed images. Fig. 5 represents the original image and Fig. 6 represents the reconstructed image of the same. The image that was originally classified as defective through binary classification will now be reconstructed to an image that will resemble the good class. Thus, classifying it into a good class will produce more images for the good class and the binary classification model can be trained even further continuously to reach higher accuracies. The kernel density and reconstructed error are useful while implementing the autoencoder as they help in classifying the reconstructed image.

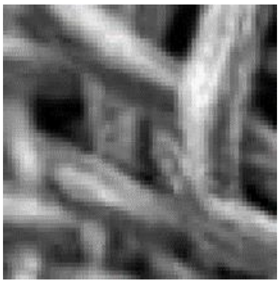

Fig. 5. Original image

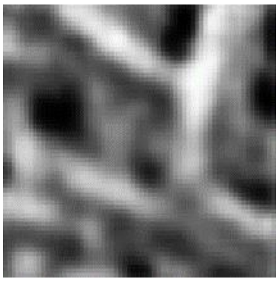

Fig. 6. Reconstructed image

5. Conclusion and future work

This study focuses on innovative strategies that can guide future researchers in designing their work. Binary and multiclass classification methods provide dynamic performance in fabric defect detection. We have implemented Convolutional Neural Networks (CNNs) to perform multiclass classification, facilitating the identification of various kinds of anomalies present in fabrics. Furthermore, the addition of autoencoders enhanced the performance of the system. Development of such a system would greatly benefit textile industries by helping them distinguish between defective and pristine fabric, thereby ensuring stringent quality control measures. The successful integration of the fabric defect detection models with Generative AI (GenAI), will contribute in generating pioneering solutions in the textile industries.

This research directly addresses the important issue of sustainable textile management, with a view of reducing global textile waste and standardizing existing systems. Our proposed framework provides tangible benefits to the textile industry, simplifies the quality control process and facilitates the development of industry-ready automation solutions for fabric defect detection. By eliminating waste and accurately identifying defects, our work contributes to the quality of the fabric and solves problems that are incurred during the manufacturing process. The advantages of binary and multiclass classification algorithms further augment the quality inspection programs in the textile industry, and ensure the support of improved quality control methods. Our innovation has the potential to revolutionize the fabric inspection landscape by providing sophisticated technology that replaces traditional visual inspection methods and will be widely adopted by textile manufacturing companies.

The future trajectory of this research will cover the implementation of novel algorithms in order to generate more accurate and satisfactory results. Moreover, expanding the size of the dataset is also an important task so as to enhance the efficiency of the defect detection systems. By incorporating a broader range of image classes, the training of the model will be comprehensive and it will be able to find even the subtle irregularities within the textiles images provided as input, augmenting the system's performance on the whole. Inclusion of a larger dataset will not only help train the model better but also will provide it with greater number of types of defects or anomalies present in the fabrics which are still currently not addressed. Additionally, our aim is to make the system and the models used, capable of real time defect detection. Doing so, will help identify if there are any kinds of defects in the fabrics produced at an earlier stage, stop the manufacturing process, and make the necessary modifications that are required.

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Conflicts of interest

The authors declare no conflicts of interest.

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