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Comparative Analysis of Suitability of Deep Learning Models in Quality Assurance of Fabrics

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Abstract: Industry 4.0 has revolutionized the manufacturing sector in India. The Textile Industry in India is a strong pillar of the Indian economy and leans on deploying Machine learning techniques to overcome its inherent challenges. Identifying defects in the fabric after production is a tedious process. The defect, if tiny, may not catch the attention of human vision. Fabric defect detection can be effectively done using image processing. This work analyses the capabilities of ten cutting-edge pre-trained convolutional neural networks for distinguishing between defective and non-defective fabrics, which is essential for assuring the quality of the fabric produced. For this purpose, we leverage the transfer learning models VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NasNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2. Fabric irregularities influence the quality of the product and consumer satisfaction. Advanced Convolutional Neural Network methods automate the detection process with reduced manual intervention, leading to standardized quality measures. We aim to determine the best-suited model for binary classification to execute the task at hand with maximum performance. This work compared improvised deep learning models by implementing them over a fabric defect dataset. This was done by fine-tuning the different models and incorporating custom layers to cater to the specific datasets. The performance of these models was evaluated using metrics such as F1-score, precision, recall, and accuracy. InceptionResNetV2 was found suitable over both defective and non-defective classes. The results of this work demonstrate the suitability of using deep learning techniques for automating fabric defect detection and, hence, the quality assurance process of fabrics.

Keywords: Fabric, Quality Assurance, Defect Detection, Transfer Learning, InceptionResNetV2, NasNetLarge, MobileNetV2

1. Introduction

The textile industry is a cornerstone of India's economy, providing significant economic, employment, and export benefits to the Nation. Assertions made in [1] endorse that the textile craftsmanship of India has been known and appreciated by the world for ages. With Industry 4.0 in place, the textile industry has also been elated with technology adaptation, automation, and improvement [2]. Real-time sensing technology, Enterprise Resource Planning Solutions, the Internet of Things, Smart manufacturing processes, and Artificial Intelligence are a few of such advancements in the Textile Industry. In [3], new technology is mentioned as a crucial element in increasing productivity and exports. Discussions in [4] suggest that AI can be deployed in the textile industry in India in several impactful ways like deployment in automating repetitive tasks, design and development, quality control, product optimization,

sustainable production, etc. Work and discussions of [5-8] reveal that the application of Convolutional Neural Network/Deep Learning algorithms has been popular in fabric defect detection in late 2024 and early 2025. Although in its preliminary stages of trial in fabric defect detection, the You Only Look Once (YOLO) series of algorithms are also deployable in fabric defect detection as studied in [9-12]. Analyzing the challenges noted in the published articles, automated quality assurance of fabrics and the choice of best models for the purpose were mentioned as research gaps worth addressing. Defect detection from fabric images was usually done using wavelet transforms, Gabor filters, and Fourier transforms [13], and Local Binary Patterns (LBP) were mainly employed for identifying texture variations and irregularities. By mid-2024, Deep Learning methods were growing popular for different types of defect detection. Convolutional Neural Networks (CNNs) in Deep Learning have risen to be an all-time favourite

among researchers for fabric defect detection, and many other similar application areas, due to the capacity to identify and extract complex features from images. The key concepts we have implemented for fabric defect detection are transfer learning and augmentation, along with different types of CNN models popularly in use.

Transfer learning trains a model on a large dataset and uses the knowledge thus gained to enhance performance on a different yet related dataset to solve a similar problem. The promising use of the Deep Learning technique was illustrated by using GoogleNet architecture on the TILDA dataset [14]. Successful use of the pre-trained CNN architecture, MobioeNetV2 was done for the classification of circular knitting fabric images using various defect types [15]. This work also mentioned that MobileNetV2 was used since it requires fewer hyperparameters than InceptionV3 and Xception, two other CNN models. In [16], pre-trained CNN models such as VGG19, ResNet152, and DenseNet161 were deployed using full-network finetuning and fixed feature extraction. This was aimed to address the need for extensive labelled data that is usually required for defect type when used with traditional deep learning methods as they require limited labelled examples and reduced time and resources for data annotations. A saliency-based approach was used in [17] to identify the defective parts of the fabric. A CNN model was deployed for fabric defect classification, to categorize the fabric as either defective or non-defective, implementing 4 convolutional layers, 4 max-pooling layers, and a Softmax activation function. Contents of [18] disclosed a Literature Review and analysis of the application of Computer Vision and Digital Image Processing in defect detection. It covered Histogram-based, colour-based, and texture-based image segmentation. The latest trends in deep learning were also covered in this review.

To address the Gradient degradation issue in Deep Networks, and reduce complexity, the faster R-CNN network using ResNet50 and FPN was implemented and compared with mainstream models in [19]. The result showed that the enhanced, advanced model served more advantageously than traditional deep learning methods. Improved local defect prediction using InceptionV1 to improve histogram equalization for localizing defects and implementing LeNet5 for global defect recognition was undertaken in [20]. To prove that Machine learning and computer vision play a leading role in automatic defect detection and classification, [21] studied VGG19 and ResNet34 and found that the VGG19 model is better at spotting detailed patterns whereas ResNet34 was better at working along with a deep neural network. Transfer learning methods can address information loss caused by pooling layers with the introduction of the capsule network. The authors [22] claim that this method can be used effectively in defect classification. The article also considers that the unavailability of high-quality annotated data and diverse

defect types hinders the effective use of deep learning in quality control of textiles.

The Segment Anything Model (SAM) is used by [23] in defect segmentation to overcome this problem. Deep Learning, employing ResNet and the VGG16 with different fabric defect datasets, was deployed in [24] to enhance generalized image understanding and localized defect detection tasks. The scarcity of defect data was solved to an extent by [25] by the development and use of stacked convolutional autoencoders, with real defective data.

Another concept worth mentioning with fabric defect detection and classification over fabric datasets is Data Augmentation, a term used alongside CNN and Transfer learning in Fabric Defect Detection. Data Augmentation boosts model generalization capabilities. While studying the fabric defect detection and classification capabilities of CNN models like VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NasNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2, the impact of data augmentation is quite significant. This can be considered as a fine-tuning strategy. According to [26], data augmentation is a strategy to prevent overfitting through regularization. Augmentation is deployed by generating new data with various orientations from a limited amount of data. It increases the size and diversity of the training dataset, and this, in turn, improves the performance and generalized use of machine-learning models. Deep Learning methods are implemented in image processing applications. In such cases, image data augmentation artificially increases the size and diversity of training datasets [27]. This helps to improve the performance and generalization ability of deep learning models, particularly when the available data is limited. Data augmentation can create new and varied instances of the training data by applying transformations like geometric transformations, colour space augmentations, kernel filters, image mixing, random erasing, and advanced techniques like GANs and neural style transfer. According to the authors of [28], image data augmentation is important for enhancing the performance and generalization of deep learning models used for computer vision-related implementations. It uses transformations and helps mitigate overfitting by artificially increasing the size and diversity of the training. This technique is especially beneficial when dealing with data with limited labeling, as it allows models to learn from a broader range of examples. This helps them in improving their ability to generalize to unseen data. Authors of [29] propose the suitability of generating real-like synthetic image data using Generative Adversarial Networks (GANs). This is a method of augmentation that we have used in this work for preparing training data for the Convolutional Neural Network (CNN). Numerous methods for image data augmentation are mentioned in [30]. The major ones include geometrical transformation, incorporating noises - like Gaussian noise and salt and

pepper noise, color changes, blurring effects, cutout, random erasing, auto augment, Rand Augment, Grid mix, mosaic, and GAN-based methods. Authors necessitate the generation of synthetic data samples using these methods to help augment the original dataset. This measure is believed to improve model performance and generalization ability, thereby mitigating overfitting in data-limited scenarios. With the scarcity of specific types of data, the data is generally unbalanced and affects effective and dependable processing and results. So, it is best to do augmentation to facilitate better image processing. Accruing concerns and suggestions from all respected authors, we concluded upon this work, an attempt to remedy the gap in Machine Learning, specifically Deep Learning model selection for fabric defect detection.

2. Materials and Methods

2.1 Dataset preparation

Kaggle's TILDA 400 dataset was deployed in this work. It originally contained images resized to 512x512 pixels. This was segmented into 64x64 patches for processing. These patches were further categorized into class folders based on the distinct defect type categories such as "good," "hole," "objects," "oil spot," and "thread error." The distribution of images across these categories varied across each class with "good" (23170), "hole" (337), "objects" (873), "oil spot" (636), and "thread error" (620). The TILDA400 dataset shows that the category "good" has the most abundant images and "hole" has the least prevalence. The given dataset comprises a substantial number of images, and to work with these large numbers of images, it is recommended to have more computational resources, and it is time-consuming. To resolve these issues, the dataset is modified by making some alterations, which encompass both the addition and elimination of images to achieve the desired balance. After this modification, the number of images per class counts to 800. For the abundant classes, the targeted count is achieved by iterating through the shuffled image list and randomly deleting them. In cases where the classes had fewer than 800 images, supplementary images were either duplicated or sampled at random from the existing collection until each class was populated with 800 images. This repetitive approach persisted until the requisite image count was attained for each class. Thus, ensuring uniformity and balance in the dataset for upcoming analysis or deep learning tasks.

2.2 Methods

Data pre-processing is vital for a more precise and trustworthy fabric defect classification. This work encompasses data augmentation methods that introduce variation or diversity in the data that aid in combating overfitting by enabling the model to identify

intrinsic anomalies and key patterns. Through a data partitioning scheme of ratio 8:1:1, the model is exposed to meticulous scrutiny of novel datasets, enhancing generalization and usefulness in fabric defect identification. In fabric defect classification, pre-trained convolutional neural networks serve as a game-changer. They use their acquired knowledge to visualize features so that patterns can be perceived and irregularities in textile materials can be identified specifically. Fine-tuning these models gives better results. Numerous studies support the techniques of fine-tuning the pre-trained convolutional neural model, contributing to more robust performance in classification tasks. The following section provides a brief understanding of how different pre-trained models have helped and contributed to the previous studies in this research area:

2.2.1 VGG16

In the study of authentic handloom fabric identification [31], the utilization of VGG16 has shown good validation accuracy and lower validation loss. The deep layers of the model, which offer the ability to extract intrinsic features, are favorable for complex image classification tasks [32]. The study in [33] depicts how VGG16 showcased its wholesomeness in classifying the gearbox and also played a prominent role in the ensemble method to refine the overall performance of the model. For detecting ventricular ectopic beat episodes, as in [34], VGG16 was one of the models proposed among others that exhibited the highest specificity and precision. Due to its simplicity and depth, it is carried out for tire defect detection [35] and weave pattern classification [36].

2.2.2 ResNet50

A study of micro defect classification [37] introduces the technique of attention enhancement, which is then incorporated into ResNet50, resulting in superior performance of ResNet50. In the work in [19], the usage of ResNet50 over VGG16 has been proved to reduce the complexity and number of parameters when used for fabric defect detection. Work in [38] emphasizes that in the agricultural arena, ResNet50 vaunted its performance in the classification of corn seed diseases by addressing the vanishing gradient challenge. As ResNet50 provides the learning capabilities for image recognition, the model provides substantial improvements in specificity and F1-score for unbalanced data, integrating the universal image fusion techniques and fuzzy logic [33] of the identification of defects in the gearbox. There are two models in use under ResNet50 are:

1. *InceptionV3*: The model can handle multiple filter sizes, along with its parallelized convolutions, making it rewarding for diverse crack sizes and locations [39]. The model can

work well across sketchy and inconsistent data, helping in distinguishing between melanoma and non-melanoma [40], which can aid experts in early diagnoses and offer effective treatment. Its ability to extract intrinsic features from images assists in identifying defects in circular knitting fabrics [41], tires [35], and gearboxes [33]. The utilization of two-phase deep learning and fine-tuning of the model addresses complex issues facing recognition in gestures, making it apt for limited resource constraints [42]. Its application lies across multiple sectors, including livestock farming for identifying camel faces [43], computer vision for character recognition like Modi Script [44], healthcare for detecting normal and abnormal heart signals [34], etc.

- ii. *Xception*: The model provides a more coherent design, making it applicable for complex detail capture in Modi character recognition [44]. The deep learning approach to brain tumor classification based on the Xception model yields prominent results compared to other models, demonstrating its powerful differentiating capabilities [45]. Due to the training of the model on a large dataset, the model exhibits robust and generalized recognition of emotion [46] and also immense potential in the analysis of EGG data. This study [47] indicates that the Xception model outperforms other models based on its characteristics, and its integration with IoT can deal with real-time crack detection. The model addresses the detection of tires, regardless of varying specifications, designs, and defect types, achieving solutions that outperform other models in recall, precision, accuracy, and F1-score across both validation and testing datasets [35].

2.2.3 InceptionResNetV2

The work in [47] has implemented InceptionResNetV2 and shown successful learning on finite data. The model contributed to the high performance of the system in defect detection. The model's architecture enhances the data sorting process and eases the packaging of high-quality data [48]. The model is good at categorization of pictures, saving time and resources for the task at hand. It is especially superior in recognizing various oral health issues [49]. This model was also used to aid healthcare professionals in the classification of lung disease in post-COVID-19 patients [50]. Features from the CT scan images were extracted and integrated to capture multi-scale features. The improvised model has also proved its ability to classify handloom fabrics [31], tire defects [35], and abnormal VEB episodes [17].

2.2.4 DenseNet121

DenseNet121 demonstrates exceptional performance based on the accuracy rate for cauliflower disease classification [51], granting valuable insights for agricultural development and monitoring systems. By encouraging transfer learning, DenseNet121 opens a new course for convenient and timely healthcare interventions. This reliability in medical diagnosis helps the model to achieve its superiority in the accurate prediction of acute pneumonia [52]. There is also a study that witnessed the strength of the model across MobileNet in classifying diverse coral reefs [53]. The modification of DenseNet improves the industrial part classification by accommodating SE-blocks to extract the weights of the feature and enhances the original DenseNet [54]. In the classification of multiple diseases affecting the tomato leaves [55], the modified DenseNet121 is recognized for optimizing the hyperparameters using the PSO algorithm, which makes efficient utilization of memory and processing resources.

2.2.5 NasNetLarge

In the performance evaluation done for identifying abnormal and VEB episodes [25], the model took the longest computational time but showed a high recall rate for the detection of VEB episodes. For sustainable livestock farming, i.e., camel face identification [34], the model makes use of depth-wise separable convolutions and auxiliary classifiers that help in gradient propagation while training. In the study [56], focusing on feature-based interpretation based on CNN, NasNetLarge is compared with other models like InceptionV3, relieving its robust performance across various datasets and its singular dependency criterion in the decision-making process. Among various architectures studied [57] in transfer learning with pre-trained models for automated prostate cancer detection, this model emerged as the most effective and supports pathologists in their diagnosing work.

2.2.6 EfficientNetB0

EfficientNetB0, when fine-tuned in deep learning, strikes an effective balance between accuracy and computational resources for classifying breast tumors [32]. Utilizing transfer learning shapes the model to be resourceful and structured. Since the model is renowned for its balanced scaling of resolution, width, and depth, it improves the recognition of different human emotions [58].

EfficientNetB0 showcases its superiority over MobileNetV2 and ResNet50 for classification of vehicles based on small datasets over training and validation accuracy [59]. It also exposes the dynamic adaptations and overcomes overfitting issues. [60] claims the model is dependable since it could predict COVID-19 remarkably well from X-ray images.

2.2.6 EfficientNetB3

This architecture offers improved flexibility so that we can mold them according to the task at hand by adding sufficient custom layers. With the guidance of global maximum pooling and batch normalization techniques, the model achieved its generalization and convergence to categorize ocular conditions such as cataracts, normal vision, diabetic retinopathy, and glaucoma in the medical field [61]. There is a study that focuses on the development of crop growth and yields with the utilization of transfer learning of EfficientNetB3. As it displays excellence at depth and exploits fewer parameters, the model is acceptable in telling apart whether the leaves are healthy or crooked [62]. The EfficientNetB3 model is also advantageous in supporting global food security, which integrates the ensemble learning method to improve the prediction of plant diseases when compared to the individual models [63].

2.2.7 MobileNetV2

Its feature extraction capabilities are manipulated as an encoder to accomplish end-to-end fabric defect segmentation [64]. To attain computational competence, MobileNetV2 utilizes depth-wise separable convolutions as it lessens the number of parameters and calculations required, which leads to better classification of fabric defects in circular knitting fabrics [41]. Its application is extended in areas like the medical field, agricultural and crop management, automotive, and many more. For detecting abnormal and ventricular ectopic beat episodes, which are crucial for cardiac patients [34], outlined high classification accuracy in low computational time. It is employed to escalate the classification of corn seed diseases [38] by fine-tuning the MobileNetV2, making use of its inverted residual

structure for robust performance, and addressing challenges like limited dataset size and class imbalance. In the context of tire defect identification, the model is designed to be suitable for mobile and resource-limited environments, with its architecture fine-tuned and optimized for both efficiency and speed. [35].

2.2.7 Experimental Setup

This section provides the details required to perform a comparative analysis of 10 different transfer learning models for binary classification of textile fabric defects. The experiment was carried out on Google Colab, utilizing the Google Compute Engine (GCE) backend. The computational environment involves 12.7 GB of system RAM and a GPU with 15.0 GB of RAM, guaranteeing efficient processing of intensive machine-learning tasks. The experiment utilized Python 3, TensorFlow, and Keras for model building and training, alongside libraries such as NumPy and Pandas for data manipulation, and Matplotlib for visualization. We selected ten pre-trained models: VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NASNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2, initializing them with ImageNet weights and adding a classification head suitable for the fabric dataset. By training each model for 35 epochs with accuracy and loss being tracked, ensuring a thorough evaluation and delivering valuable performance data for different models.

2.3 Methodology

For the automated textile fabric detection process, the data to be used is collected from the Kaggle environment, which is a public dataset named "TILDA 400."

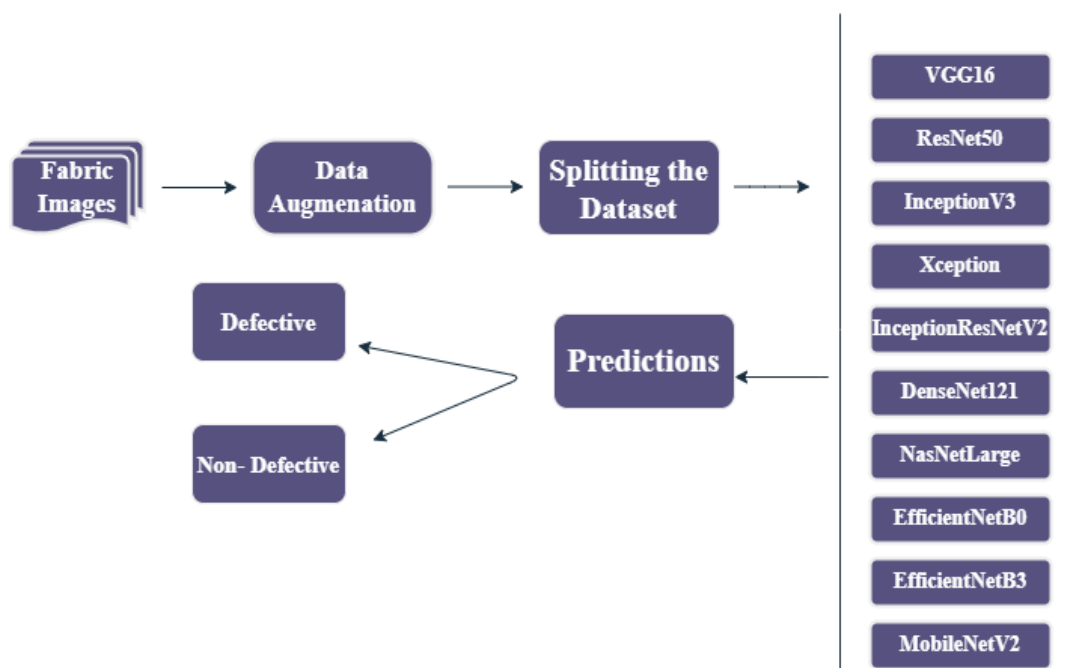


Figure 1. Methodology of the proposed work

This dataset is tailored to identify defects and organize information within the context of the fabric industry. In the modified dataset, the five classes - "good," "hole," "objects," "oil spot," and "thread error" - are divided into defective and non-defective categories. In this work, we present a comprehensive implementation study of multiple pre-trained models, DenseNet121, EfficientNetB0, EfficientNetB3, InceptionResNetV2, InceptionV3, MobileNetV2, NasNetLarge, ResNet50, Xception, and VGG16, ascertaining their suitability in fabric defect classification. The comparative study of these models helps to understand the suitability of the model architecture in the domain and the specific problems. The methodology followed in this work is illustrated in Figure. 1.

3. Implementation

The dataset after splitting was subjected to training utilizing the 10 pre-trained models, i.e., VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NasNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2. The architecture of these models is illustrated in Figure. 2. Models such as VGG16, ResNet50, DenseNet121, EfficientNetB0, and MobileNetV2 have an input size of 224 x 224, while InceptionV3, Xception, and InceptionResNetV2 share a similar input size of 299 x 299. In contrast, NasNetLarge and EfficientNetB3 require input sizes of 331 x 331 and 300 x 300, respectively. For robust performance and generalization, our study consists of freezing the base layers of the corresponding model and applying custom layers to these models for binary classification using single sigmoid output, which includes GlobalAveragePooling2D layers, dense layers with different numbers of units (128, 256, 512, 1024), and dropout layers with different rates (0.3, 0.5). The global average pooling layers are used in all models to reduce the dimensionality in feature maps, and dense layers are introduced for feature evolution and unification along with the development of non-linearity using activation functions like ReLU. To avoid the chances of overfitting, the regularization technique that involves dropout layers is comprehended. All models apply an early stopping technique to stop training when the performance stops improving and helps restore the best weights. Batch normalization is added in the NasNetLarge model as its architecture is more complex, which aids in stabilizing each layer, allowing training to be faster and more robust. The customized layers included flattening layers, dense layers, dropout layers, and an output layer for the binary classification task. During the compilation, Adam optimizers were utilized with a specified learning rate. Since the task to be achieved is binary classification, binary cross entropy was used, and for evaluating the model performance, the primary metrics were taken as accuracy. Each model was trained according to the specifications, and their performances were noted. The

evaluation was conducted using a validation set and a test set. All models were assessed using precision, recall, F1-score, and a confusion matrix, which assessed their effectiveness in classifying defective and non-defective samples. Test accuracy is a primary metric, but a detailed evaluation reveals that the models tend to perform significantly better for the defective class compared to the non-defective class. Figure 2 depicts the architecture of different models. Adding custom layers improves the performance and efficiency of carrying out the binary classification task. This approach reduces the need for substantial computational resources as well as training large datasets from scratch.

4. Results and Discussion

Graph plots of training and validation accuracy of each model help us better understand the suitability and performance differences. The plots are prepared for each implementation over each epoch. Figure 3 below depicts the training and validation accuracy plot, and Figure. 4 presents the training and validation loss plot. These metrics offer valuable insights into how well the model learns the pattern and how it will behave on a new dataset, representing the concept of transfer learning. This work implements different deep-learning models for pre-training and classification over a trimmed dataset of fabric images. For classification, the fabric image has to be determined as defective or non-defective, which is a binary classification. Analysis of classification results will provide insights into the model's performance and efficiency for the intended purpose and help to choose the best model for fabric defect detection and classification. The evaluation metrics used in this work for performance analysis of the ten refined deep learning models on the fabric image dataset are precision, accuracy, recall, and F1-score, concerning the predictions based on the test set.

Table 1 and Figure. 5 indicate the performance metrics of the 10 models we deployed on the dataset for the classification task. From the results in the table, we can observe how the models perform for the binary classification task, i.e., defective vs. non-defective.

From the above consolidations, it is evident that the MobileNetV2 model performed well for the defective class, achieving high precision and recall rates of 0.80 and 0.98 respectively, and an F1 score of 0.88. However, it shows poor performance for the non-defective class. VGG16 is better in identifying defective classes and has a slight improvement in identifying non-defective classes with a precision of 0.23, recall of 0.17, and F1-score of 0.20. DenseNet121 achieves a test accuracy of 82.50% with adequate performance for defective classes. A balanced performance is exhibited by the Xception and NasNetLarge models as shown in Table 1, in handling defective and non-defective classes in terms of precision and recall.

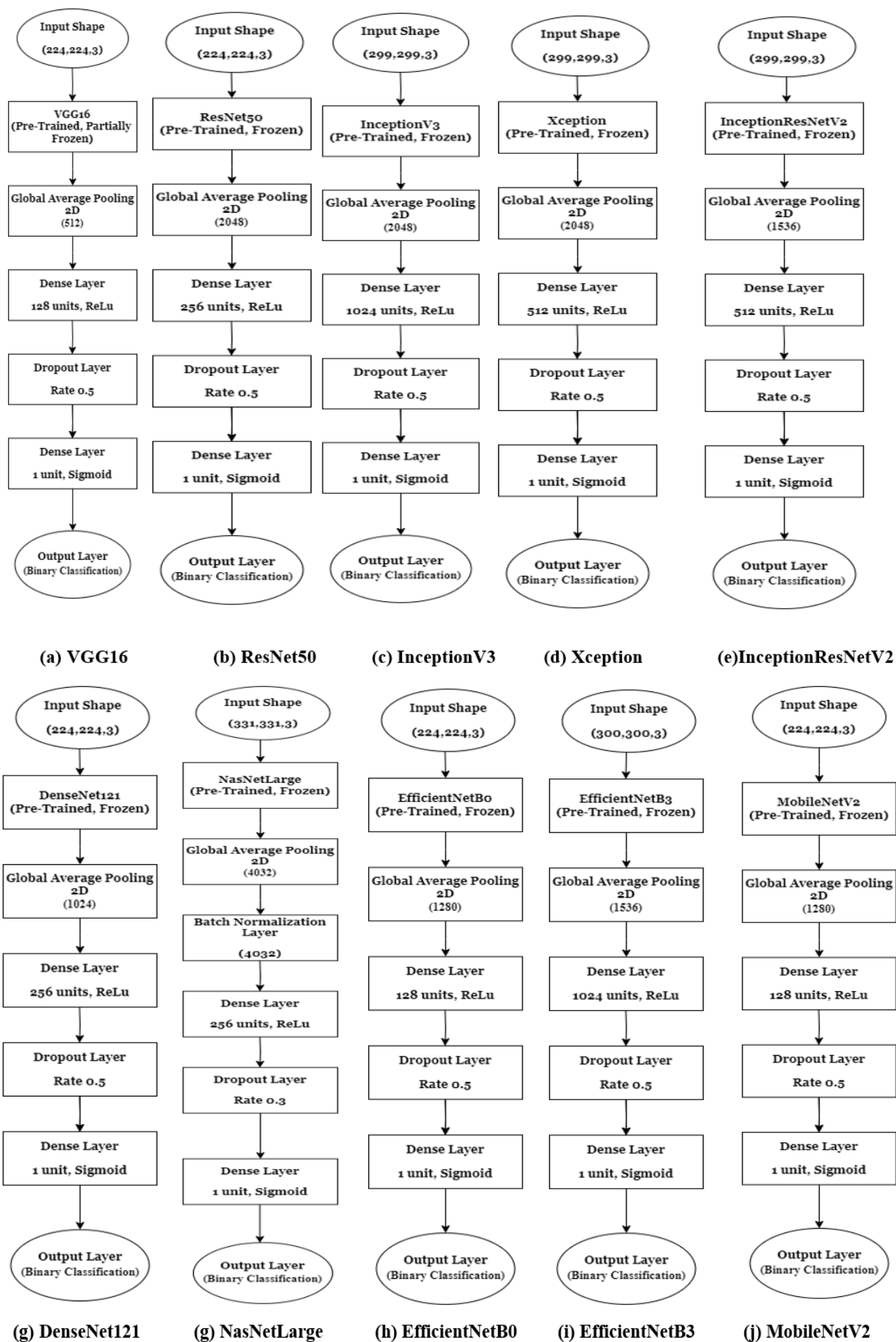
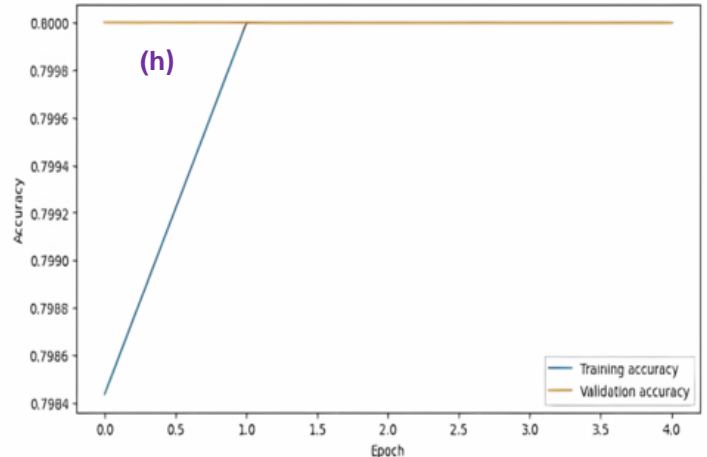
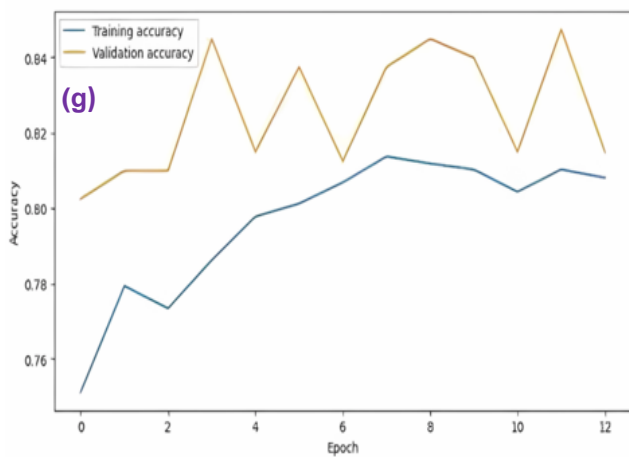
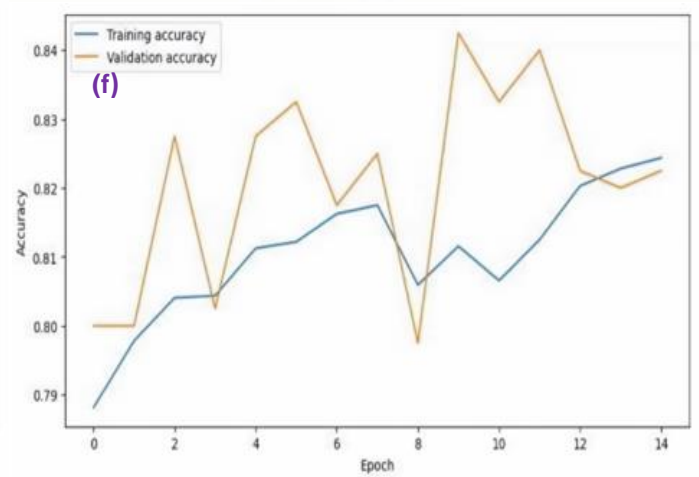
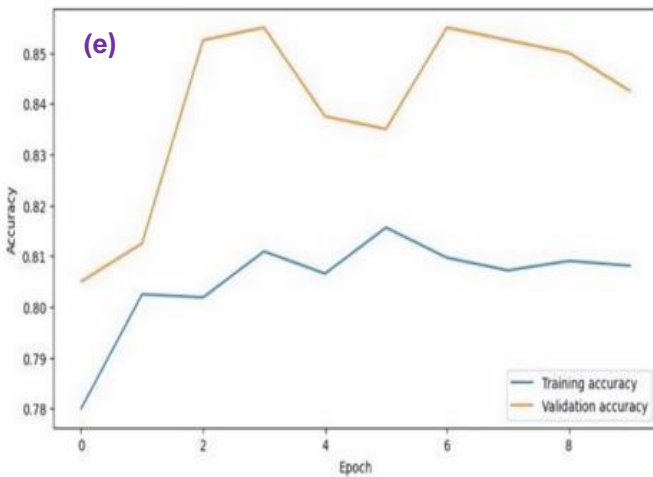
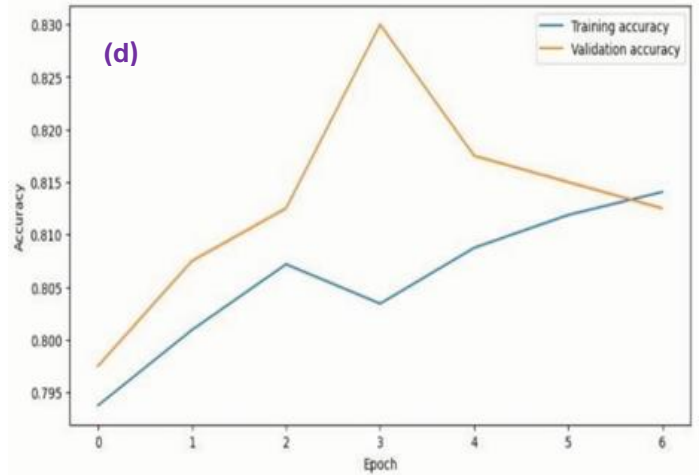
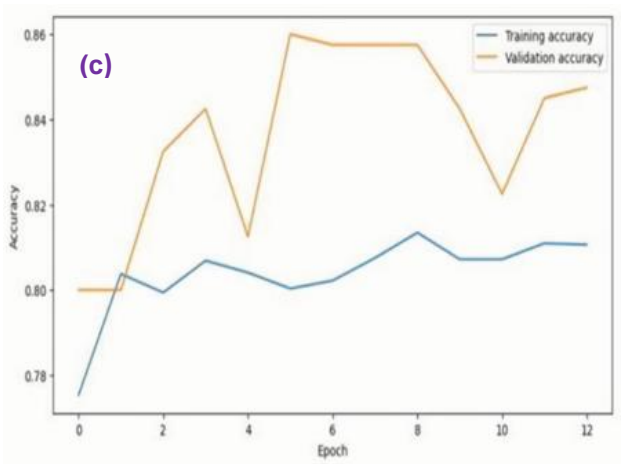
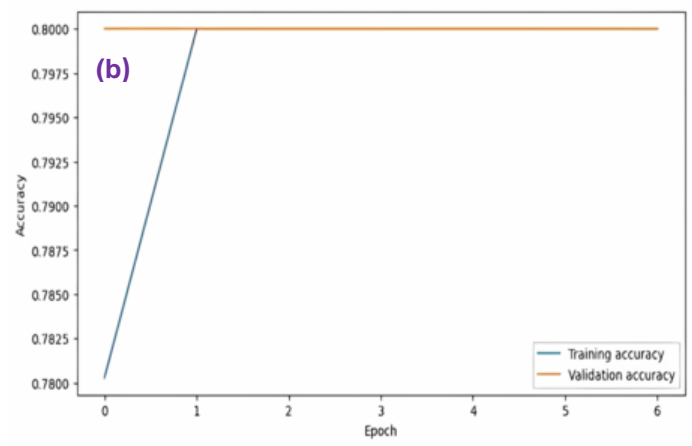
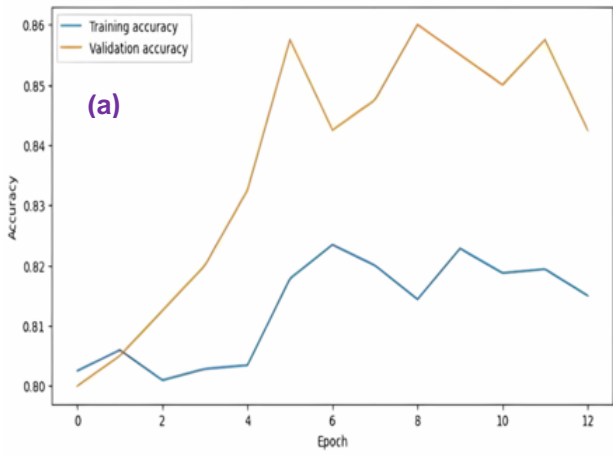


Figure 2. Architecture of the proposed Models



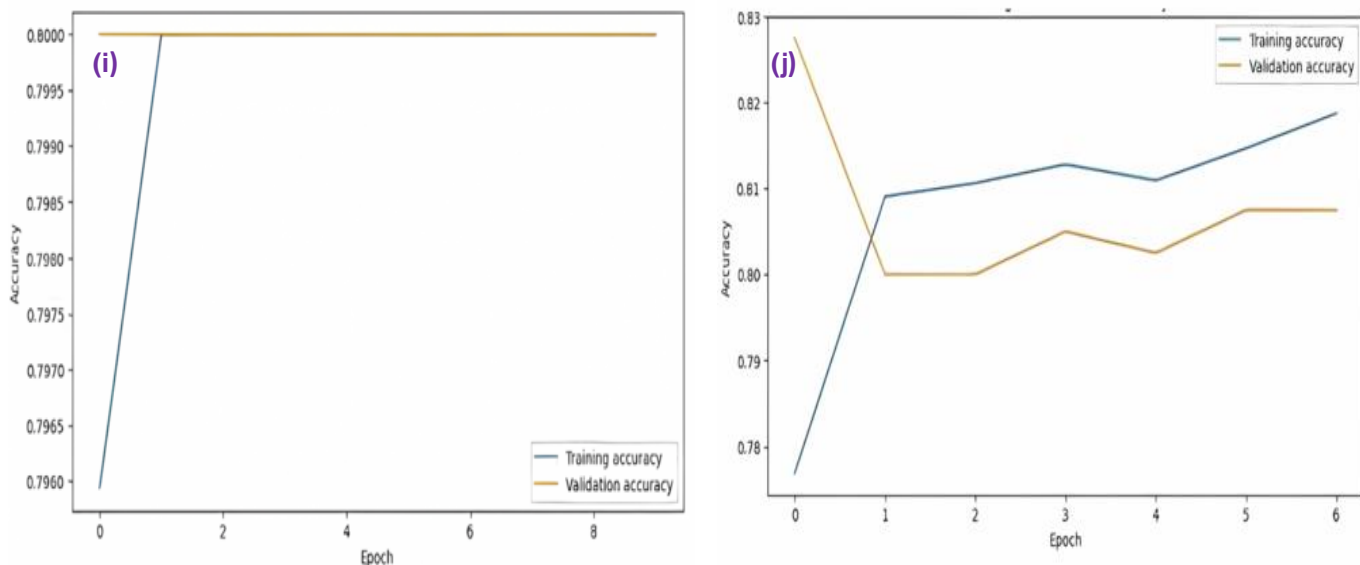
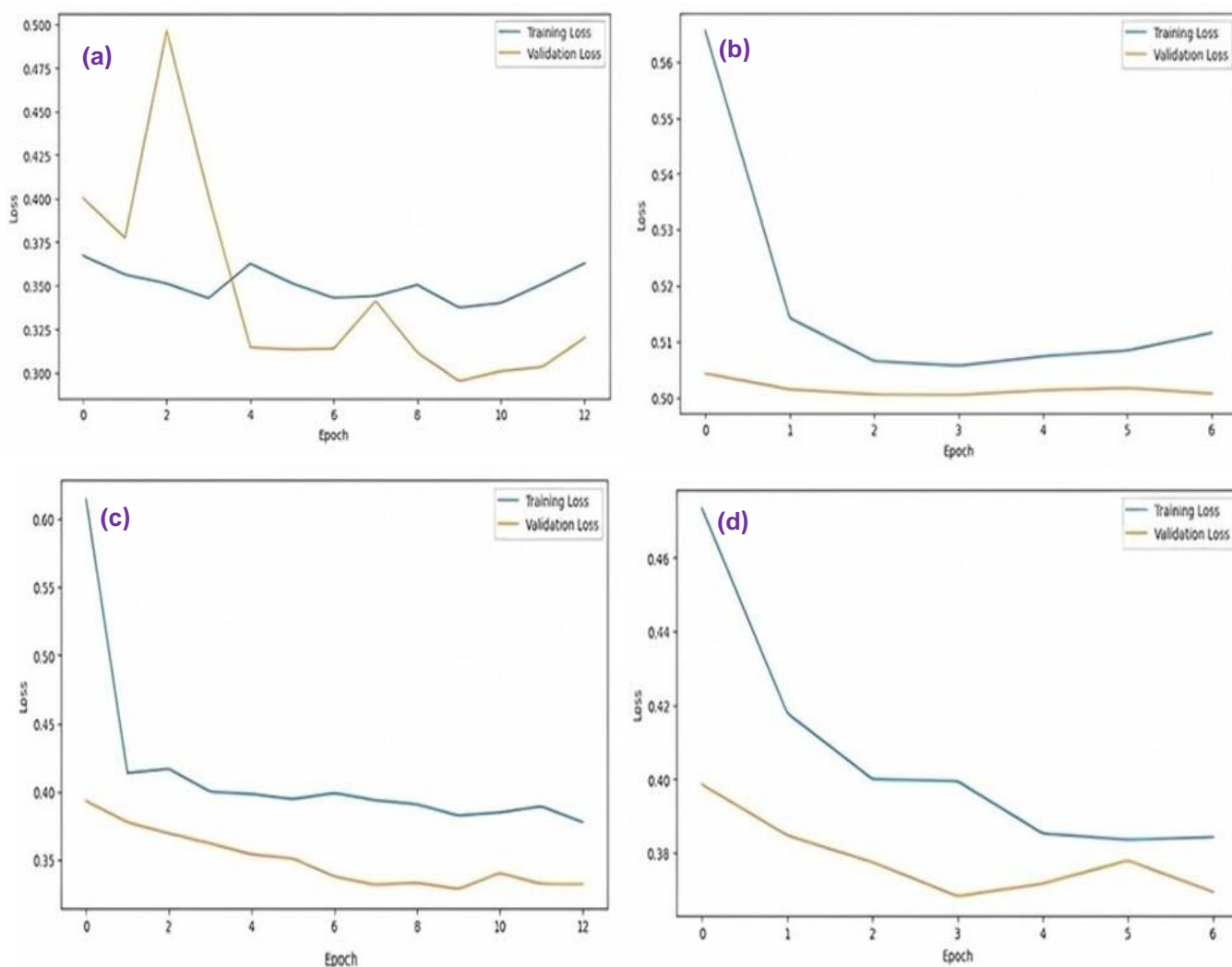


Figure 3. Training and Validation Accuracy of the Proposed Models (a) VGG16, (b) ResNet50, (c) Inception V3, (d) Xception, (e) InceptionResNetV2, (f) DenseNet121, (g) NasNetLarge, (h) EfficientNetB0, (i) EfficientNetB3 (j) MobileNetV2



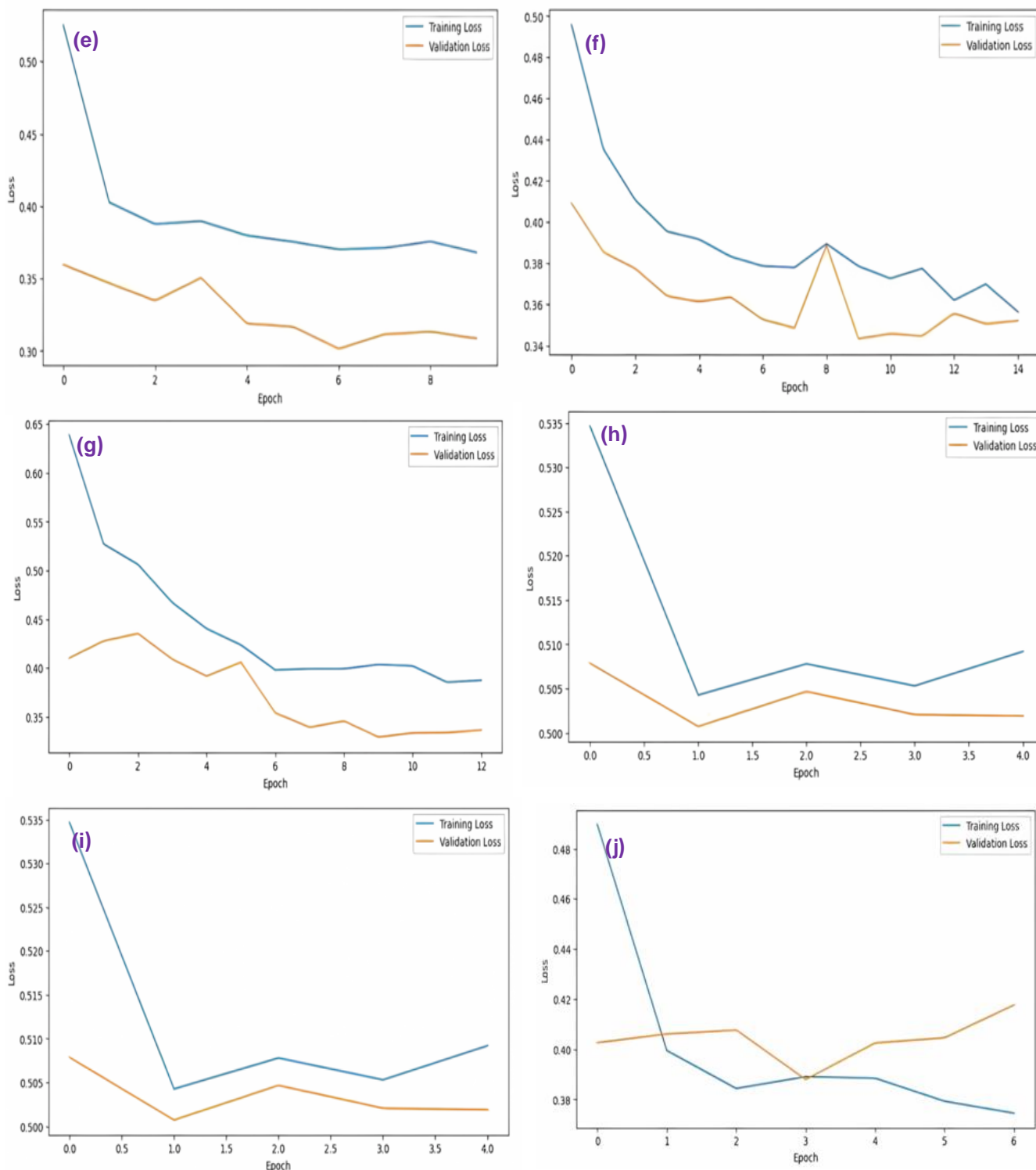


Figure 4. Training and Validation Loss of the Proposed Models (a) VGG16, (b) ResNet50, (c) InceptionV3, (d) Xception, (e) InceptionResNetV2, (f) DenseNet121, (g) NasNetLarge, (h) EfficientNetB0, (i) EfficientNetB3, (j) MobileNetV2

The models, including ResNet50, EfficientNetB0, and EfficientNetB3, demonstrate perfect precision, recall, and F1 scores for the defective class. However, they do not accurately identify the non-defective class. This shows that the architecture of these models is not the right choice for identifying the non-defective class.

In InceptionV3, the precision and recall are comparatively high for defective rather than non-defective, with a test accuracy of 80.5%. In this study, InceptionResNetV2 proves to be the best-performing model concerning both defective and non-defective classes, with a test accuracy of 85.75%.

Table 1. Results of fabric defect classification performance of different models

Models	Accuracy	Precision		Recall		F1-Score	
		Defective	Non-Defective	Defective	Non-Defective	Defective	Non- defective
VGG16	0.71	0.80	0.23	0.85	0.17	0.83	0.20
ResNet50	0.80	0.80	0.00	1.00	0.00	0.89	0.00
InceptionV3	0.77	0.80	0.23	0.94	0.07	0.86	0.11
Xception,	0.72	0.81	0.23	0.85	0.17	0.83	0.20
InceptionResNetV2	0.77	0.81	0.33	0.92	0.16	0.86	0.22
DenseNet121	0.74	0.80	0.20	0.90	0.10	0.85	0.13
NasNetLarge	0.74	0.81	0.26	0.89	0.15	0.85	0.19
EfficientNetB0	0.80	0.80	0.00	1.00	0.00	0.89	0.00
EfficientNetB3	0.80	0.80	0.00	1.00	0.00	0.89	0.00
MobileNetV2	0.79	0.80	0.33	0.98	0.04	0.88	0.07

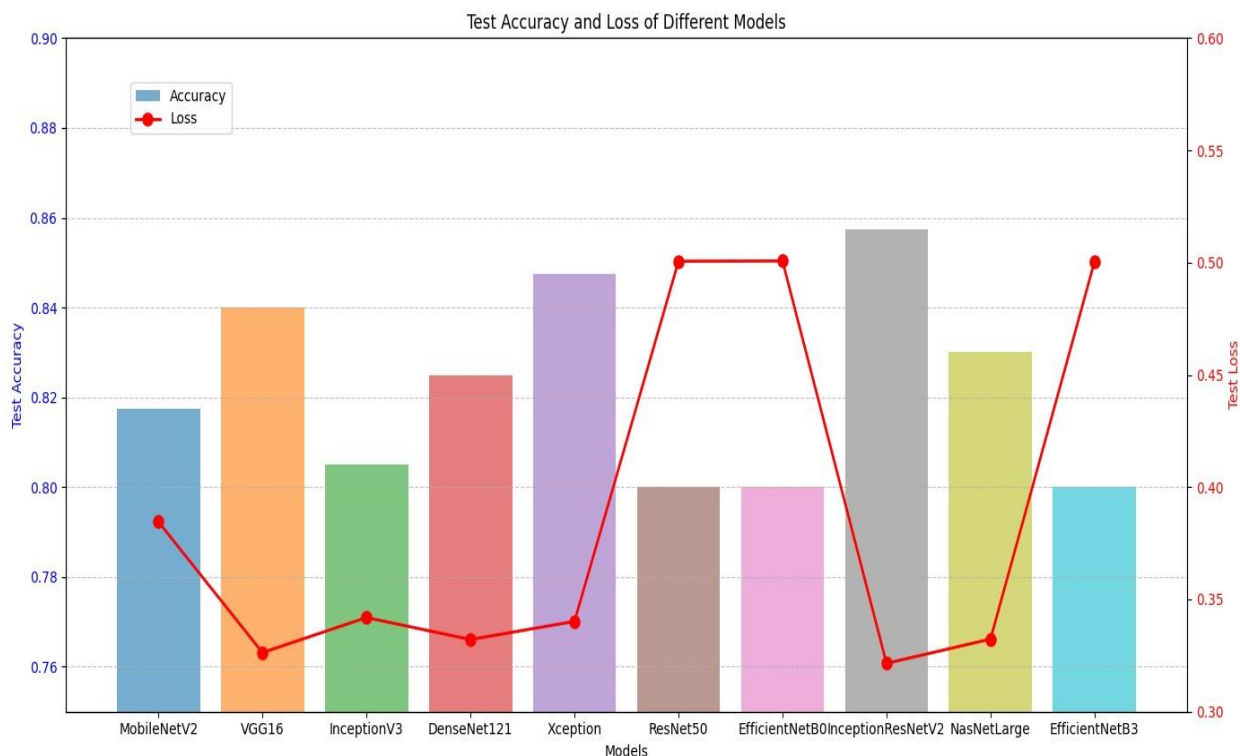


Figure 5. Results of the implemented models over Test Accuracy and Loss

Table 2. Summary of performance of the models

Models	Defective Class	Non-Defective Class
VGG16	Good	Average
ResNet50	Good	Poor
InceptionV3	Good	Average
Xception,	Average	Average
InceptionResNetV2	Good	Good
DenseNet121	Good	Average
NasNetLarge	Average	Average
EfficientNetB0	Good	Poor
EfficientNetB3	Good	Poor
MobileNetV2	Good	Poor

It also shows a better balance in handling the non-defective class, with a precision of 0.81 for defective and 0.33 for non-defective, recall of 0.92 for defective and 0.16 for non-defective, and F1-score of 0.86 for defective and 0.22 for non-defective classes. A summary of the findings is given in Table 2 above.

Observing the output of all validation metrics, we can infer that InceptionResNetV2 is the best suitable for fabric defect detection and classification.

4.1 Comparison with similar work

Below given is Table 3 which is a consolidation of comparison of our work with similar recent works. From the table, it is obvious that even though the works are in fabric defect detection, they try to solve it by a different means. The concerns, objectives and results of each of the works are also different. It may also be noted that Convolutional Neural Networks and Transfer Learning algorithms as well as their modified versions are gaining attention with fabric defect detection due to better performance in classification.

Table 3. Comparison of Results with Similar Works

Reference And Year	Objective/Work	Methodology/ Dataset	Results/Claim/Conclusion
[65] and 2024	Visual features of the normal fabric surface were studied. Defect region identification is done.	For studying Visual features, FDD via multi-scale memory-augmented auto-encoder (MemAE) Fusion was implemented. KNN, DeepSVDD and a refined model were used to implement defect detection. Result evaluation is done using the Periodic-pattern fabric database and the Yarn-dyed fabric database.	Precision, Recall, Accuracy, and F-measures show that the improved method gives above 94% over all evaluation metrics and hence is proven over other methods used in the work.
[66] and 2024	Texture defect Detection (TDD) Algorithm was Implemented for defect detection. Statistical features extracted using Gray Level Co-occurrence Matrix are input in Support Vector Machine for defect classification.	TILDA Dataset (partial) was used for the study. 4 classes of defects were identified.	With test images from TILDA dataset, defect detection accuracy was 96.56% and with the live, actual photographs captured, it was 97%. Hence the models and methods implemented are claimed successful.
[67] and 2024	A live and real-time system for defect detection and monitoring.	Live image capturing and CNN based defect classification	Claimed classification accuracy is 96.92%
[68] and 2024	Implement CNN for fabric defect detection. Tries to improve reliability and generalization ability. Developing a new machine learning specialized network to reduce the decision action for LSTM based on	Usage of TEXFED dataset mentioned.	Figure based claims not made. Evaluations not mentioned. Software interface of segmentation and image enhancement shown. Betterment claimed.

	CNNs.		
[69] and 2024	Optimal Artificial Neural Network-based Fabric Defect Detection and Classification (OANN-FDDC) technique, with noise removal and augmentation, is implemented on two datasets.	A comparative analysis of the OANN-FDDC algorithm is done with CNN, ResNet50v2, DenseNet159v2, FPN, Bi-FPN, NAS-FPN, DenseFPN, and i-FPN over two datasets.	The comparison of results shows clear supremacy of the OANN-FDDC algorithm over the others, considering accuracy, precision, recall, and F1 scores.
[70] and 2022	Using improved YOLO V4 model for fabric defect detection	Improved YOLO V4, Improved YOLO V4 without CLAHE, YOLO V4 SSD, and faster R-CNN were implemented. Defect classes were hole, line, float, and stain.	Different types of Fabric Defect Classes identified using four algorithms. Improved YOLO V5 showed maximum accuracy with 86.5%. Improved YOLO V4 gave the best results for float type defect with scores – AP = 99.84%, Precision = 98.48%. Recall = 99.90% and F1 = 99.00%
[71] and 2022	"DetectNet", a modified CNN model for defect detection, is used with images of fabric surfaces	TILDA Dataset (partial) was used for the study.	Accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve were analyzed. All were above 0.9 for both models, implemented on the TILDA dataset, and hence the models are claimed to be effective.
OUR WORK and 2024	The suitability of enhanced pre-trained CNN models was studied over the reduced TILDA dataset. Ten Transfer learning algorithms were implemented and analyzed for suitability over fabric defect detection.	Reduced TILDA dataset was used, and performance evaluation of ten Transfer learning models - VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NasNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2 were done.	Based on performance and evaluation metrics, Accuracy, Precision, Recall, and F1-scores, all the improvised transfer learning models scored fairly well with respect to accuracy and loss functions. InceptionResNetV2 was found to have better accuracy over both defective and non-defective classifications.

5. Conclusion

The work presented in this paper is about gaining comparative knowledge in the binary classification of fabrics into defective and non-defective with the utilization of ten different transfer learning models: VGG16, ResNet50, InceptionV3, Xception, InceptionResNetV2, DenseNet121, NasNetLarge, EfficientNetB0, EfficientNetB3, and MobileNetV2. The collected images from the dataset were first augmented to suit the purpose and resources. The augmented datasets were then divided into a training set, validation set, and test set. During the training process, the transfer learning models were fine-tuned by freezing the base layers of the corresponding models and inserting custom layers involving a global average pooling layer, a dense layer, dropout layers, and finally a single output layer to carry out the binary classification task. This helped the

model to enhance its performance. As a result, we observed that InceptionResNetV2 exhibits balanced handling of the defective and non-defective classes with a test accuracy of 85.75%, thus proving to be the best model among the others to perform binary classification. After InceptionResNetV2, the second-best model that balanced well was NasNetLarge and Xception in terms of precision and recall. Other models performed well for defective classes but showed poor performance for non-defective classes. The drawbacks we faced in this study were the unbalanced classes and the limited availability of labeled datasets. Future improvements in this area include ensuring the availability of labeled data with balanced classes and introducing ensemble methods for detecting multiple defect types, locations, and sizes across various fabric materials, leveraging deep learning and artificial intelligence.

6. Limitations and future work

With the emergence of Industry 4.0, there has been a rapid technological evolution in the Textile industry. Many manual tasks could be automated with real-time decision-making and greater precision. This stipulates rules and best practices for financial gains relevant to the industry. However, no industry or method is perfect. The general challenges faced in automated fabric defect detection are a large number of different fabric types, the difference in properties of each type, undistinguishable defect and background texture, low contrast between defects and texture surface, variations in image acquisition, low-resolution images, size and shape of images, computational complexity, image acquisition method, etc. Limitations of manual defect inspection, dataset quality, and variations in visual perception of the image, diversity of fabric types, imbalance of defect classes, complex patterns of fabrics, computational costs and storage requirements, and real-time deployment in high-speed production environments are another set of challenges that need addressing. These real-world challenges necessitate the development of robust, efficient, and adaptable deep-learning models for effective fabric defect detection in real-world manufacturing settings. In this work, we have proposed a method to overcome the limitations of manual sorting of defective fabrics. An image processing application is implemented, which captures and processes digital images of the fabric. Ten named transfer learning models implementing deep learning mechanisms are deployed over a size-reduced dataset of defective and non-defective fabrics. The accuracy of this binary classification task is assessed using precision, recall, and F1 scores. Also, accuracy is plotted. Inferences made based on the metrics prove InceptionResNetV2 as the best model for satisfactory classification results over defective and non-defective classes. Our findings provide solutions for only a small part of the real-world computational challenges in fabric defect detection. The processing requirements, algorithms, and modifications for specific datasets may vary. The scope for future and extended work is varied since many finer details are worth addressing. Requirements for large storage, complex processing, methods to distinguish between different texture types and prints, different fabric finish, including considerations for thickness and interleaving pattern and closeness of thread, normalizing specific image characteristics for uniform processing, fine-tuning models, using an ensemble of methods for providing solutions, etc. require close attention and evolution by research. The work, results, and findings presented in this paper can be a strong base for upcoming research in fabric defect detection.

References

- [1] Kanupriya, Linkages among trade, gender and environment: A review in the context of India's textile sector. *Decision*, 51(3), (2024) 397-409. <https://doi.org/10.1007/s40622-024-00397-w>
- [2] W.H. Tsai, H.C. Chen, S.C. Chang, K.C. Chan, (2024). Revolutionizing Textile Manufacturing: Sustainable and Profitable Production by Integrating Industry 4.0, Activity- Based Costing, and the Theory of Constraints. *Processes*, 12(11), (2024) 2311. <https://doi.org/10.3390/pr12112311>
- [3] P. Raichurkar, M. Ramachandran, Recent trends and developments in textile industry in India. *International Journal on Textile Engineering and Processes*, 1(4), (2015) 47-50.
- [4] Reenu, S. Singh, S. Vig, S. Dwivedi, (2024). Impact of uses of Artificial Intelligence (AI) in Textile Industry in India. In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, Kamand, India. <https://doi.org/10.1109/ICCCNT61001.2024.10725995>
- [5] N. Ingle, W.J. Jasper, A review of the evolution and concepts of deep learning and AI in the textile industry. *Textile Research Journal*, 95(13-14), (2025) 00405175241310632. <https://doi.org/10.1177/00405175241310632>
- [6] S. Wang, Y. Xu, H. Zheng, B. Li, High-Precision Fabric Defect Detection via Adaptive Shape Convolutions and Large Kernel Spatial Modeling. *arXiv*. <https://doi.org/10.48550/arXiv.2501.14190>
- [7] X. Li, Y. Zhu, A real-time and accurate convolutional neural network for fabric defect detection. *Complex and Intelligent Systems*, 10(3), (2024) 3371-3387. <https://doi.org/10.1007/s40747-023-01317-8>
- [8] S.S. Mohammed, H.G. Clarke, (2024) Advanced Convolutional Neural Network Approach for Fabric Defect Detection. In 2024 Innovations in Intelligent Systems and Applications Conference (ASYU), IEEE, Ankara, Turkiye. <https://doi.org/10.1109/ASYU62119.2024.10757038>
- [9] C. Chen, Q. Zhou, S. Li, D. Luo, G. Tan, Fabric defect detection algorithm based on improved YOLOv8. *Textile Research Journal*, 95(3-4), (2025) 235-251. <https://doi.org/10.1177/00405175241261092>
- [10] Z. Zhang, T. Huang, W. Zhang, Y. Yang, Q. Yu, DGHR-YOLO: fabric defect detection based on High-level Screening-feature Pyramid Networks and deformable convolution. *Nondestructive Testing and Evaluation*, (2025)1-26. <https://doi.org/10.1080/10589759.2025.2451768>
- [11] L. Zhou, B. Ma, Y. Dong, Z. Yin, F. Lu, DCFE-YOLO: A novel fabric defect detection method. *PloS one*, 20(1), (2025) e0314525. <https://doi.org/10.1371/journal.pone.0314525>

- [12] F. Li, K. Xiao, Z. Hu, G. Zhang, Fabric defect detection algorithm based on improved YOLOv5. *The Visual Computer*, 40(4), (2024) 2309-2324. <https://doi.org/10.1007/s00371-023-02918-7>
- [13] B. Eker, S. Erdal, (2018). Image processing technique in fabric defect control applications on textile industry. Center for Quality.
- [14] A. Beljadid, A. Tannouche, A. Balouki, Fabric defect classification using transfer learning and deep learning. *International Journal of Artificial Intelligence*, 12(3), (2023)1379.
- [15] K. HANBAY, Classification of Circular Knitting Fabric Defects Using MobileNetV2 Model. *Türk Doğa ve Fen Dergisi*, 12(4), (2023) 63-68. <https://doi.org/10.46810/tdfd.1327971>
- [16] M.S. Minhas, J.S. Zelek, Defect Detection using Deep Learning from Minimal Annotations. In *Visigrapp*, 4, (2020) 506-513.
- [17] A. Zahra, M. Amin, F.E.A. El-Samie, M. Emam, Efficient utilization of deep learning for the detection of fabric defects. *Neural Computing and Applications*, 36(11), (2024) 6037-6050. <https://doi.org/10.1007/s00521-023-09137-0>
- [18] A. Rasheed, B. Zafar, A. Rasheed, N. Ali, M. Sajid, S. Dar, U. Habib, T. Shehryar, M.T. Mahmood, Fabric defect detection using computer vision techniques: a comprehensive review. *Mathematical Problems in Engineering*, 2020, (2020) 1-24. <https://doi.org/10.1155/2020/8189403>
- [19] Z. Jia, Z. Shi, Z. Quan, M. Shunqi, Fabric defect detection based on transfer learning and improved Faster R-CNN. *Journal of Engineered Fibers and Fabrics*, 17, (2022) 15589250221086647. <https://doi.org/10.1177/15589250221086647>
- [20] X. Jun, J. Wang, J. Zhou, S. Meng, R. Pan, W. Gao, Fabric defect detection based on a deep convolutional neural network using a two-stage strategy. *Textile Research Journal*, 91(1-2), 130-142. <https://doi.org/10.1177/0040517520935984>
- [21] P. Sajjanshetti, C. Patil, M. Naik, M. Waghmare, S. Gaikwad, (2024). Automated Fabric Defect Detection (No. 12723). EasyChair.
- [22] Y. Kahraman, A. Durmuşoğlu, A. Classification of defective fabrics using capsule networks. *Applied Sciences*, 12(10), (2022) 5285. <https://doi.org/10.3390/app12105285>
- [23] Z. Chen, W.K. Wong, Z. Zhong, J. Liao, Y. Qu, (2023). Effective Transfer of Pretrained Large Visual Model for Fabric Defect Segmentation via Specific Knowledge Injection. *arXiv*. <https://doi.org/10.48550/arXiv.2306.16186>
- [24] S.R. Arshad, M.K. Shahzad, Deep Learning Based Fabric Defect Detection. *Research Reports on Computer Science*, (2024)1-11.
- [25] Y.J. Han, H.J. Yu, Fabric defect detection system using stacked convolutional denoising auto-encoders trained with synthetic defect data. *Applied Sciences*, 10(7), (2020) 2511. <https://doi.org/10.3390/app10072511>
- [26] K. Maharana, S. Mondal, B. Nemade, A review: Data pre-processing and data augmentation techniques. *Global Transitions Proceedings*, 3(1), (2022) 91-99. <https://doi.org/10.1016/j.gltp.2022.04.020>
- [27] C. Shorten, T.M. Khoshgoftaar, A survey on image data augmentation for deep learning. *Journal of big data*, 6(1), (2019) 1-48. <https://doi.org/10.1186/s40537-019-0197-0>
- [28] T. Kumar, R. Brennan, A. Mileo, M. Bendechache, Image data augmentation approaches: A comprehensive survey and future directions. *IEEE Access*, IEEE, 12, (2024) 187536-187571. <https://doi.org/10.1109/ACCESS.2024.3470122>
- [29] M.A.I. Fahim, S.A. Tumpa, M.K. Newaz, Object Detection Using Machine Learning And Neural Networks.
- [30] W. Zeng, Image data augmentation techniques based on deep learning: A survey. *Mathematical Biosciences and Engineering*, 21(6), (2024) 6190-6224. <https://doi.org/10.3934/mbe.2024272>
- [31] L.B. Mahanta, D.R. Mahanta, T. Rahman, C. Chakraborty, Handloomed fabrics recognition with deep learning. *Scientific Reports*, 14(1), (2024) 7974. <https://doi.org/10.1038/s41598-024-58750-z>
- [32] A. Heikal, A. El-Ghamry, S. Elmougy, M.Z. Rashad, Fine tuning deep learning models for breast tumor classification. *Scientific Reports*, 14(1), (2024) 10753. <https://doi.org/10.1038/s41598-024-60245-w>
- [33] A.H. Barshooi, A. Yazdaniyoo, E. Bagheri, A. Moosavian, (2024) Imbalanced Data Classification with Fuzzy Logic and Universal Image Fusion for Gearbox Defect Detection. In 2024 20th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP) IEEE, Babol, Iran, Islamic Republic of Iran. <https://doi.org/10.1109/AISP61396.2024.10475291>
- [34] N. Sriraam, A. Srinivasulu, Performance evaluation of convolution neural network models for detection of abnormal and ventricular ectopic beat cardiac episodes. *Multimedia Tools and Applications*, 83(24), (2024) 65149-65188. <https://doi.org/10.1007/s11042-023-17997-w>
- [35] R.A. Saleh, M.Z. Konyar, K. Kaplan, H.M. Ertunç, End-to-end defect detection model based on transfer learning techniques. *Neural Computing and Applications*, 36(20), (2024)12483 -12503. <https://doi.org/10.1007/s00521-024-09664-4>

- [36] N. Akram, R.A. Butt, M. Amir, Modification of a convolutional neural network for the weave pattern classification. *Mehran University Research Journal of Engineering & Technology*, 43(2), (2024) 79-90. <https://doi.org/10.22581/muet1982.2998>
- [37] S. Lin, Z. He, L. Sun, A novel micro-defect classification system based on attention enhancement. *Journal of Intelligent Manufacturing*, 35(2), (2024) 703-726. <https://doi.org/10.1007/s10845-022-02064-2>
- [38] M. Alkanan, Y. Gulzar, Enhanced corn seed disease classification: leveraging MobileNetV2 with feature augmentation and transfer learning. *Frontiers in Applied Mathematics and Statistics*, 9, (2024) 1320177. <https://doi.org/10.3389/fams.2023.1320177>
- [39] S. Usharani, R. Gayathri, U.S.D.R. Kovvuri, M. Nivas, A.Q. Md, K.F. Tee, A.K. Sivaraman, An efficient approach for automatic crack detection using deep learning. *International Journal of Structural Integrity*, 15(3), (2024) 434-460. <https://doi.org/10.1108/IJSI-10-2023-0102>
- [40] E. Bazgir, E. Haque, M. Maniruzzaman, R. Hoque, Skin cancer classification using Inception Network. *World Journal of Advanced Research and Reviews*, 21(02), (2024) 839-849. <https://doi.org/10.30574/wjarr.2024.21.2.0500>
- [41] M.H. VARJOVI, M.F. TALU, K. HANBAY, Fabric Defect Detection Using Customized Deep Convolutional Neural Network for Circular Knitting Fabrics. *Türk Doğa ve Fen Dergisi*, 11(3), (2022) 160-165.
- [42] B. Karsh, R.H. Laskar, R.K. Karsh, mIV3Net: modified inception V3 network for hand gesture recognition. *Multimedia Tools and Applications*, 83(4), (2024) 10587-10613. <https://doi.org/10.1007/s11042-023-15865-1>
- [43] D. Gerdan Koc, C. Koc, H.E. Polat, A. Koc, Artificial intelligence-based camel face identification system for sustainable livestock farming. *Neural Computing and Applications*, 36(6), (2024) 3107-3124.
- [44] R. Sonavane, P. Ghonge, S.U. Patil, K.S. Sagale, A.A. Maha, Exploring ResNet101, InceptionV3, and Xception for Modi Script Character Classification. *International Journal of Intelligent Systems and Applications in Engineering*, 12(17s), (2024) 117-124.
- [45] A. Mohamed, M. Rabea, A. Sameh, E. Kamal, (2024). Brain Tumor Radiogenomic Classification. *ArXiv*.
- [46] A. Phukan, D. Gupta, Deep feature extraction from EEG signals using xception model for emotion classification. *Multimedia Tools and Applications*, 83(11), (2024) 33445-33463. <https://doi.org/10.1007/s11042-023-16941-2>
- [47] H.W. Hridoy, M.M. Rahman, S. Sakib, A framework for industrial inspection system using deep learning. *Annals of Data Science*, 11(2), (2024) 445-478. <https://doi.org/10.1007/s40745-022-00437-1>
- [48] W.K. ElHelew, D. Abo-Bbakr, S. Zayan, M.A. Mayhoub, Classification of Dates Quality Using Deep Learning Technology Based On Captured Images. *MisrJournal of Agricultural Engineering*.41(3), (2024) 225-242. <https://doi.org/10.21608/mjae.2024.286079.1137>
- [49] J. Rashid, B.S. Qaisar, M. Faheem, A. Akram, R.U. Amin, M. Hamid, Mouth and oral disease classification using InceptionResNetV2 method. *Multimedia Tools and Applications*, 83(11), (2024) 33903-33921. <https://doi.org/10.1007/s11042-023-16776-x>
- [50] A. Sanampudi, S. Srinivasan, Local search enhanced optimal Inception- ResNet- v2 for classification of long-term lung diseases in post-COVID-19 patients. *Automatika*, 65(2), (2024) 473-482. <https://doi.org/10.1080/00051144.2023.2295142>
- [51] N.R. Pradhan, H. Ghosh, I.S. Rahat, J.V.N. Ramesh, M. Yesubabu, (2024). Enhancing Agricultural Sustainability with Deep Learning: A Case Study of Cauliflower Disease Classification. *EAI Endorsed Transactions on Internet of Things*, 10. <https://doi.org/10.4108/eetiot.4834>
- [52] A. Sanampudi, S. Srinivasan, Local search enhanced optimal Inception- ResNet-V2 for classification of long-term lung diseases in post-COVID-19 patients. *Automatika*, 65(2), (2024) 473-482. <https://doi.org/10.1080/00051144.2023.2295142>
- [53] H.P. Hadi, E.H. Rachmawanto, R.R. Ali, Comparison of DenseNet-121 and MobileNet for Coral Reef Classification. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, 23(2), (2024) 333-342. <https://doi.org/10.30812/matrik.v23i2.3683>
- [54] K. An, X. Sun, Y. Song, Y. Lu, Q. Shanguan, (2024). A DenseNet-based feature weighting convolutional network recognition model and its application in industrial part classification. *IET Image Processing*, 18(3), (2024) 589-601. <https://doi.org/10.1049/ipr2.12971>
- [55] C.A.D. Lestari, S. Anam, U. Sa'adah, Tomato Leaf Disease Classification with Optimized Hyperparameter: A DenseNet-PSO Approach. In *First International Conference on Applied Mathematics, Statistics, and Computing (ICAMSAC 2023)*, Atlantis Press. 228-239. https://doi.org/10.2991/978-94-6463-413-6_23
- [56] D. Wang, Y. Xia, Z. Yu, (2024). Feature-based Interpretation of Image Classification with the use of Convolutional Neural Networks. *IEEE Access*, IEEE. <https://doi.org/10.1109/ACCESS.2024.3397871>

- [57] P. Gifani, A. Shalhaf, (2024). Transfer Learning with Pretrained Convolutional Neural Network for Automated Gleason Grading of Prostate Cancer Tissue Microarrays. *Journal of Medical Signals & Sensors*, 14(1), (2024) 4. <https://doi.org/10.1007/s11042-023-18087-7>
- [58] R. Angeline, A.A. Nithya, Deep Human Facial Emotion Recognition: a transfer learning approach using efficientnetb0 model. *Journal of Theoretical and Applied Information Technology*, 102(8), (2024).
- [59] Q.T. Pham, D.D. Pham, K.L. Can, H.D. To, H. D. Vu, Vehicle Type Classification with Small Dataset and Transfer Learning Techniques. *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, 11(2), (2024) e2-e2.
- [60] M.A. Talukder, M.A. Layek, M. Kazi, M.A. Uddin, S. Aryal, Empowering covid-19 detection: Optimizing performance through fine-tuned efficient net deep learning architecture. *Computers in Biology and Medicine*, 168, (2024)107789. <https://doi.org/10.1016/j.combiomed.2023.107789>
- [61] P. Shourie, V. Anand, D. Upadhyay, V. Singh, S. Gupta, (2024) Leveraging the capabilities of efficientnetb3 to classify eye diseases with reliability. In 2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), IEEE, 1-5. <http://dx.doi.org/10.1109/ICAECT60202.2024.10469017>
- [62] A. Kaur, V. Kukreja, N. Thapliyal, M. Aeri, R. Sharma, S. Hariharan, (2024) Pre-trained VGG16 and EfficientNetB3 for Multiclass Classification of Orange Leaf Diseases. In 2024 3rd International Conference for Innovation in Technology (INOCON), IEEE, Bangalore, India.1-6. <https://doi.org/10.1109/INOCON60754.2024.10511701>
- [63] M.S. Chandrasekar, M. Thenmozhi, R. Sandya Sree, N. Pradeepika, Multi Plant Disease and Classification with Enhanced Efficientnet B3 Using Deep Learning Techniques.
- [64] J. Jing, Z. Wang, M. Rättsch, H. Zhang, Mobile-Unet: An efficient convolutional neural network for fabric defect detection. *Textile Research Journal*, 92(1-2), (2022) 30-42.
- [65] K. Wu, L. Zhu, W. Shi, W. Wang, Automated fabric defect detection using multi-scale fusion MemAE. *The Visual Computer*, 41, (2025)723-737. <https://doi.org/10.1007/s00371-024-03358-7>
- [66] T. Meeradevi, S. Sasikala, (2024). Automatic fabric defect detection in textile images using a labview based multiclass classification approach. *Multimedia Tools and Applications*, 83(25), (2024) 65753-65772.
- [67] M. Kulkarni, P.C. Cholke, P. Vasmatkar, S. Tambe, S. Anuse, S. Telgote, (2024) Fabric Defect Detection System Using Image Processing. In 2024 1st International Conference on Cognitive. Green and Ubiquitous Computing, IEEE, 1-7. <https://doi.org/10.1109/ic-cgu58078.2024.10530850>
- [68] P. Yashini, G. Karthika, T. Sunitha, R. Berlin Magthalin, R. (2024) Machine Learning-Based Textile Fabric Defect Detection Network. In 4th International Conference on Sustainable Expert Systems, IEEE, Kaski, Nepal, 1470-1477. <https://doi.org/10.1109/ICSES63445.2024.10763088>
- [69] N. Sajitha, S.P. Priya, Optimal Artificial Neural Network-based Fabric Defect Detection and Classification. *Engineering, Technology & Applied Science Research*, 14(2), (2024)13148-13152. <https://doi.org/10.48084/etasr.6773>
- [70] Q. Liu, C. Wang, Y. Li, M. Gao, J. Li, A fabric defect detection method based on deep learning. *IEEE access*, 10, (2022) 4284-4296. <https://doi.org/10.1109/ACCESS.2021.3140118>
- [71] A. Beljadid, A. Tannouche, A. Balouki, (2022). Automatic fabric defect detection employing deep learning. *International Journal of Electrical and Computer Engineering*, 12(4), (2022) 4129. <http://doi.org/10.11591/ijece.v12i4.pp4129-4136>

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Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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