National College of Ireland

Identification and Classification of Electrical Components on Printed Circuit Boards Using Transfer Learning

MSc Research Project
MSc in Data Analytics

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Identification and Classification of Electrical Components using Transfer Learning

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Abstract

Electronic circuit boards are becoming part of most modern-day equipment such as computers, mobile phones, autonomous cars, manufacturing equipment, etc. With the advancement of technology, printed circuit boards (PCBs) are becoming smaller and densely packed with a variety of electronic components. Given their central part in the operation of all digitally enabled equipment it is extremely necessary to inspect them for any manufacturing defect before they are released to the end consumer. It is important to accurately identify and classify the components on the PCBs before they can be inspected for any defect. Manual or mechanical inspection is both time-consuming and inefficient. Existing automated visual inspection methods are trained on datasets that do not capture real-world scenarios such as illumination and scale variation. The aim of this research is to develop a model which can accurately identify the electrical components on a printed circuit board in real-world scenarios. To achieve this, a challenging dataset has been used which contains images of PCB components from three variable aspects. They are illumination, image scale, and image sensor. Five modern transfer learning models have been implemented and their performance is evaluated. The models are InceptionV3, EfficientNetB1, EfficientNetB2, Xception and ResNet152V2. The models are optimized and evaluated on the basis of accuracy, precision, recall and F1-score.

Keywords: - Electrical components, Transfer Learning, Image classification, Printed Circuit Boards.

1 Introduction

Modern-day equipment is increasingly getting digitalized and a variety of electronic components are being introduced to make them autonomous. Printed circuit boards (PCBs) form a core part of these electronic components. With improvements in the manufacturing process, these PCBs are getting packed with a greater number of electrical components which increases their power and computing capability. However, this makes the PCBs incredibly complex and extremely delicate. They require rigorous monitoring during the manufacturing process in order to avoid faulty circuit boards being released to end customers. Manual monitoring of such delicate electrical components is time-consuming, error-prone, and not very efficient. Automatic monitoring and fault detection will solve the problems associated with manual monitoring. The first step in this approach is to accurately identify and classify the PCB parts automatically because many times components do not have proper markings and individual sub-components in a complex PCB cannot be identified easily with the naked eye.

Recent advancements in machine learning and deep learning technologies have provided many tools and techniques which can be applied to automatic object identification and classification from images (Hatcher & Yu, 2018). Computer vision-based models are now increasingly being applied to a host of problems such as food identification, traffic signal automation, industrial fault detection, etc (Wang, et al., 2020). Among various deep learning models, for computer vision-based problems, convolutional neural networks (CNNs) have shown the most promise in identifying and classifying objects from images. Their ability to extract features from images makes them the most suitable learning model for this type of task. However, CNN based neural networks require a huge amount of data in order to train properly and provide predictions with reasonable accuracy. Also, these models require huge computing resources and large training time which can be cost-prohibitive.

The primary problem with component identification is the lack of a suitable large dataset with proper labelling. Training a CNN based model with a small dataset will lead to poor accuracy and will not be suitable for production deployment. The solution to this problem is to use transfer learning-based techniques (Liu, et al., 2021). The idea behind these models is to apply the target dataset to a model which has already been trained on a larger related dataset. CNN based models expect images as their input. Images of all kinds share certain low-level features among themselves such as edges, corners, curves, etc. Once a model is trained with a sufficiently large image dataset to extract such features, it can then be supplied with a smaller specific dataset that would have properly labelled images of required objects. The model will then adjust its parameters to extract the high-level features and train its parameters to recognize the new components. It will not only save time but also be computationally very economical to implement.

The benefits of transfer learning are a reduction in training time, a high learning rate because the model has been pre-trained for similar tasks, less data requirement, and higher accuracy. Hence in this research, it is proposed to study five transfer learning models with a high accuracy rate. A challenging public dataset that incorporates images of PCB components taken under a variety of real-world scenarios is used to optimize the model for real-world application. The four proposed models are InceptionV3, EfficientNetB1, EfficientNetB2, Xception and ResNet152V2. These models have been trained with a large image dataset called ImageNet which consists of over 1.4 million labelled images.

1.1 Research Question

To what extent can transfer learning models help to improve the identification and classification of printed circuit board electrical components to help the industry automate monitoring and maintenance.

1.2 Research objectives

Table 1: Research objectives

Objectives	Description
Objective 1	A critical review of current work done for automated visual component identification and classification
Objective 2	Model design and methodology
Objective 3	Exploratory data analysis and data pre processing
Objective 4	Model implementation and evaluation
Objective 4.1	InceptionV3 model implementation and evaluation
Objective 4.2	EfficientNetB1 model implementation and evaluation
Objective 4.3	EfficientNetB2 model implementation and evaluation
Objective 4.4	Xception model implementation and evaluation
Objective 4.5	ResNet152V2 model implementation and evaluation
Objective 5	Comparison of developed models

1.3 Contribution

This research aims to develop a transfer learning model which will be specially trained for complex component identification and accurate classification. It will aid in further improvement of automated monitoring and maintenance of complex printed circuit boards (PCB).

2 Literature Review

2.1 Introduction

With the progress of industrial technology, modern-day equipment is becoming more and more intelligent. This is achieved by using digital chips which are capable of processing complex sets of instructions. These items need to be extremely perfect in order to work reliably. Hence, they need a careful inspection for any defect during the manufacturing stage. However, these components come in various sizes and are complex in design. The first step in this automation process is the proper identification of individual parts. Only after proper identification the diagnosis and maintenance of any part can be done.

2.2 CNN based models for identification and classification

Manual inspection and other invasive methods have a lot of disadvantages. Hence, other non-invasive methods using deep learning have been developed. The most promising field in this regard is an image-based analysis using convolutional neural networks (CNN). This is a deep learning model which has the ability to automatically extract features from an image using convolution layers. In power grid transmission lines automatic component identification and fault detection are done by analyzing images in a convolutional neural network based deep learning model (Zheng, et al., 2020). This model takes images of sections of the transmission grid and then these are fed to a Faster R-CNN model which performs the image analysis. Faster R-CNN is an improved version of CNN that creates a region proposal network (RPN) using a convolution layer from which to extract features instead of traversing the entire picture pixel by pixel. This reduces training and processing time.

Computer-aided diagnosis of skin diseases is performed using convolutional neural network-based models (He, et al., 2019). In this model two datasets containing 10,218 and 19,807 images are used for model training. After using an ensemble method based on a variety of CNN models the best training accuracy achieved is about 79% and the testing accuracy is about 53%. This demonstrates the problem of using smaller datasets in model training.

(Walkoli, et al., 2021) have proposed a new algorithm called scale-invariant feature transform. It uses CNN for object detection and intelligently adds labels to those images by matching those features to features from an image dataset containing labelled images. It uses the content-based image retrieval (CBIR) technique. This model requires a huge dataset for model training and is useful only for simple object identification containing a single object in the image. When the image contains multiple objects the accuracy of the model rapidly decreases.

2.3 Application of transfer learning for component identification

Although CNN-based image analysis models show promising results, they require huge datasets for training the neural network. Another problem with such modelling is the model is trained for a specific area of interest. The model is not directly suitable for object detection in some other areas. A new object class will require another model trained on a large dataset containing images from the object group of interest. Such training requires huge computing resources and a large training time. This approach is not sustainable. Hence a new approach based on transfer learning is being developed which uses a pre-trained model and uses a smaller image dataset for fine-tuning its parameters to identify specific objects of interest. Since all images have similar low-level features such as curves, edges, corners, etc, it is possible to train a model on a large image dataset to fine-tune its weight parameters to extract such low-level features. Then custom classifier layers are added to this model after which the subject-specific smaller target image dataset is supplied. The earlier layers extract low-level features and new layers extract high-level features. The model does not revisit weights in its earlier layers. This sharply reduces training time and the model is also perfected for the specific group of images.

(Rafiq, et al., 2020) have developed a scene classification method using a pre-trained model called AlexNet Convolutional Neural Network. This model is supplied with a labelled image dataset having five classes batting, bowling, boundary, crowd, and close-up. The accuracy of this transfer learning model is about 94%. Synthetic aperture radars (SAR) aid in target recognition by capturing optical, non-optical, and hybrid optical data. However, these data have a lot of noise and a traditional CNN model is not able to extract meaningful features from such a dataset. (Ying, et al., 2020) have used the transfer learning technique by using a pre-trained model which is optimized for extracting low-level features and then using SAR dataset the model is optimized for recognizing various objects. The accuracy of the model is verified to be over 97%.

Transfer learning provides the benefit of using a better trained initial model, high learning rate because the model is already trained for similar tasks, high accuracy after training, and solution to the problem of a smaller target dataset.

2.4 Existing PCB inspection methods

There are two types of PCB inspection methods currently in practice: - electrical testing and automated visual inspection.

In the electrical inspection process, PCB design parameters are checked at specified locations during manufacturing (Moganti & Ercal, 1995). It cannot detect any impurities introduced to PCB components during later stages of manufacturing. It is also not possible to test all the PCBs in a manufacturing plant. Automated visual inspection provides a solution to this problem. It uses computer vision algorithms to compare the images of PCBs with a certified and defect-free image of PCB in order to identify issues (Lim, et al., 2019).

(Xie, et al., 2013) have proposed a model based on genetic programming to detect component placement defects in a PCB. (Guerra & Villalobos, 2001) have proposed to create a 3D shape of the PCB in order to identify and classify individual components. It is tested on a dataset of 4,840 components. The problem with all these automated visual inspection methods is that they are performed on very small datasets and they do not capture the real-world scenarios a model is expected to face while performing its job such as device angle, illumination, image scale, image variance, etc.

2.5 Conclusion

PCB components come in a variety of colors, sizes, shapes, and orientations. Along with this, advanced technology has allowed the packing of smaller and greater number of components on a printed circuit board. The PCB boards themselves come in various shapes, sizes, and colors. Existing methods and techniques do not take into consideration environmental factors such as illumination, image variance, or image scale which have a high impact on model accuracy. Hence, in this paper, a challenging dataset that incorporates all such possibilities is used. In this paper application of transfer learning-based CNN models are explored to develop a suitable model which will aid in industrial component identification and classification.

3 Research Methodology

This section describes the approach, implementation, and evaluation of the project. In this research project, Knowledge Discovery in Database (KDD) methodology is used for the classification of PCB components

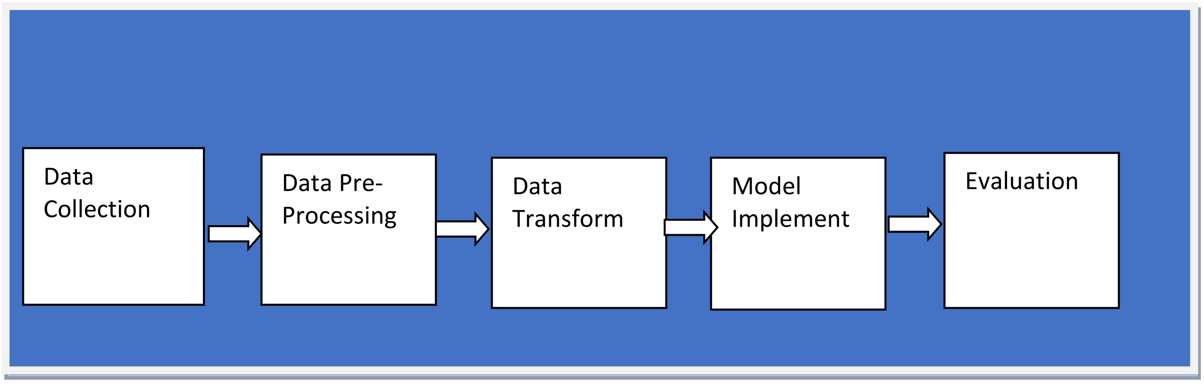

Figure-1: KDD methodology

3.1 Data Collection

The dataset has been sourced from trust-hub organisation. The specific dataset used in this research project is: - **FICS-PCB: A multimodal image dataset for automated printed circuit board visual inspection.** This dataset contains images of PCB components taken from a variety of printed circuit board samples. These images have been taken under various conditions to facilitate performance evaluation in challenging scenarios that are likely to be encountered in practice. The dataset has component images in the following six classes: - capacitors, diodes, ICs, inductors, resistors, and transistors. These images have been taken using two pieces of equipment: - a digital microscope and a Digital Single Lens Reflex (DSLR). In order to create real-world scenarios, the images were taken with variations in illumination and variations in scale. Under the microscope, three different intensities of 20, 40, and 60 using the built-in ring light have been used to capture images. Along with these three different magnifications of 1x, 1.5x, and 2x have been used to include variations in scale. The total number of images in all six classes is 28,972.

3.2 Data Pre-Processing

The original images from any single PCB sample were stored in a folder named after the PCB number. All these images were renamed and collated under six folders for easy processing. The dataset is highly imbalanced. The dataset has a large number of samples for only two classes: - capacitors and resistors. Using the dataset as it is will make the models very good at recognizing the most common components and poor at recognizing other less frequent components. Before increasing the minority component classes artificially, the original dataset is split into training and test datasets. 70% of images from each component class are stored in the training dataset and 30% are stored in the test dataset.

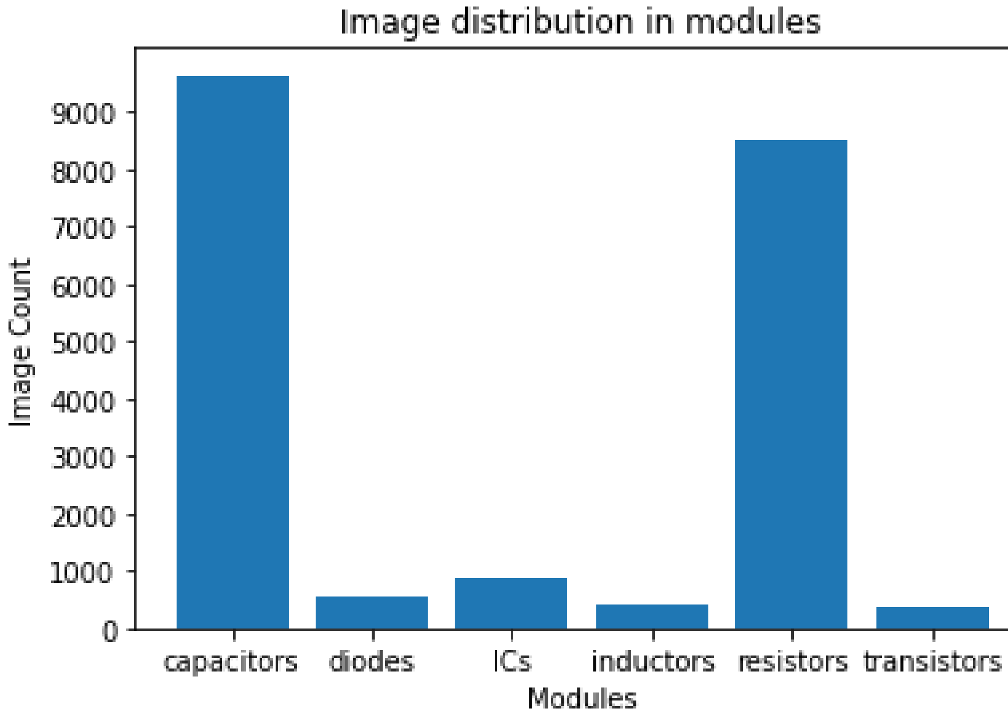

Figure-2: Component count in training dataset classes after train-test split

3.3 Data Transformation

Deep learning models require huge datasets in order to train well. However, since the data available is small in size, several augmentation operations have been performed which will artificially increase the size of the dataset. Oversampling is done on diodes, ICs, inductors, and transistors in order to bring the image count similar to capacitors and resistors to balance the classes. All images in these four classes were converted to red, green, and blue images. Then the images were rotated by 90, 180, and 270 degrees. After synthetic oversampling the training dataset is further subdivided into training and validation datasets in a ratio of 75%:25%.

After data augmentation, all the images were transformed to have uniform characteristics which will aid the model to perform consistent analysis on all the images. Scaling the images to the appropriate size is necessary because if the images are too large then it takes a lot of time and processing power for model training and the difference in image size makes it very hard for the model to learn features. Hence all the images in the training, validation, and test dataset were converted to a uniform size of 150x150 pixels. After the data pre-processing training set has 32767 images, the validation set has 10922 images and the test set has 8691 images.

3.4 Model Implementation

The transfer learning models have been chosen based on their complexity, speed, Top-1 and Top-5 accuracy. Based on these following 5 transfer learning models have been chosen for experimentation: - InceptionV3, EfficientNetB1, EfficientNetB2, Xception, ResNet152V2.

Table-2: Model comparison

Model Name	Complexity	Speed	Top-1 Accuracy	Top-5 Accuracy
InceptionV3	Low	High	77.9%	93.7%
EfficientNetB1	Low	High	79.1%	94.4%
EfficientNetB1	Low	High	80.1%	94.9%
Xception	Low	High	79.0%	94.5%
ResNet152V2	Low	High	78.0%	94.2%

In the transfer learning technique, the early layers of the chosen model are frozen and the later layers are either modified or new custom classifier layers are added as per requirement. The four proposed pre-trained models have similar modifications to their technical architecture. However, the custom layers have been fine-tuned from model to model in order to check improvement in accuracy. Experiments have been performed using a combination of different values for different hyperparameters in order to assess model performance. The different hyperparameters are cost function, optimizer, activation function, and learning rate. Final parameter values for the models have been described in the implementation section.

3.5 Evaluation

In order to compare the models F1-score metric is taken into consideration. F1-score is the harmonic mean of precision and recall. It also takes into account how the data is distributed. Since the data in six component classes is a little imbalanced, F1-score will provide a better assessment of model performance.

4 Design and Implementation Specification

This section discusses the hyperparameter tuning for each model and implementation details. The hyperparameters fine-tuned for these models are: - loss function, activation function, optimizer, accuracy metric, number of epochs, and batch size. In the following discussion only, the final parameters used in each model are described.

4.1 Hardware and Software used for experiments

The experiments have been performed using tools provided by Google. The dataset is stored in Google Drive and the hardware is provided by Google colaboratory. Google colaboratory pro+ subscription is taken to perform the experiments as the CPU and GPU requirement for image processing is very high. The following table describes the hardware and software used.

Table-3: Software and Hardware details

CPU Memory	51 GB
GPU Name	Tesla P100
GPU Memory	16 GB
TensorFlow version	2.8.0
Keras Version	2.7.0

4.2 InceptionV3 Model

This model acts as a multi-level feature extractor by computing 1x1, 3x3 and 5x5 convolution within the same module of the network. The output of these filters is then stacked along the channel dimension and before being fed into the next layer in the network. This model has 189 layers.

The top layer of this model is removed and a custom classification layer for the six classes is added. The last 15 layers are unfrozen in order to allow the model to fine-tune itself for the new PCB dataset. The loss function used is sparse_categorical_crossentropy, optimizer is Adam with a learning rate of 0.0001. The batch size used is 16. The model is run for 50 epochs with an early stopping parameter that monitors validation loss and has patience for 10 epochs.

4.3 EfficientNetB1 Model

This model is developed by Google AI. It is an efficient implementation in which the depth and width of the model are increased in a principled way and the model structure allows it to have very high accuracy with very few parameters. It has 186 layers and 7.9 million parameters.

The top layer of this model is removed and a custom classification layer for the six classes is added. The last 20 layers are unfrozen in order to allow the model to fine-tune itself for the new PCB dataset. The loss function used is sparse_categorical_crossentropy, optimizer is Adam with a learning rate of 0.0001. The batch size used is 16. The model is run for 50 epochs with an early stopping parameter that monitors validation loss and has patience for 10 epochs.

4.4 EfficientNetB2 Model

This model is an improvement over EfficientNetB1 and has 186 layers. The total number of parameters in this model is 80.8 million.

The top layer of this model is removed and a custom classification layer for the six classes is added. The last 10 layers are unfrozen in order to allow the model to fine-tune itself for the new PCB dataset. The loss function used is sparse_categorical_crossentropy, optimizer is Adam with a learning rate of 0.0001. The batch size used is 16. The model is run for 50 epochs with an early stopping parameter that monitors validation loss and has patience for 10 epochs.

4.5 Xception Model

The Xception model is an improvement over the inception model that replaces the inception model with depth-wise separable convolutions. It is a linear stack of depth-wise separable convolution layers with residual connections. It has a total of 81 layers and 22.9 million parameters.

The top layer of this model is removed and a custom classification layer for the six classes is added. The last 10 layers are unfrozen in order to allow the model to fine-tune itself for the new PCB dataset. The loss function used is sparse_categorical_crossentropy, optimizer is Adam with a learning rate of 0.0001. The batch size used is 16. The model is run for 50 epochs with an early stopping parameter that monitors validation loss and has patience for 10 epochs.

4.6 ResNet152V2 Model

This model has 307 layers with 60.4 million parameters. Even though it is a very deep network the actual size of the model is quite small due to the use of global average pooling. It tackles the problem of vanishing gradient and accelerates the speed of training.

The top layer of this model is removed and a custom classification layer for the six classes is added. The last 10 layers are unfrozen in order to allow the model to fine-tune itself for the new PCB dataset. The loss function used is sparse_categorical_crossentropy, optimizer is Adam with a learning rate of 0.0001. The batch size used is 16. The model is run for 50 epochs with an early stopping parameter that monitors validation loss and has patience for 10 epochs.

5 Evaluation

5.1 InceptionV3

The following figures describe the accuracy and loss trend for InceptionV3

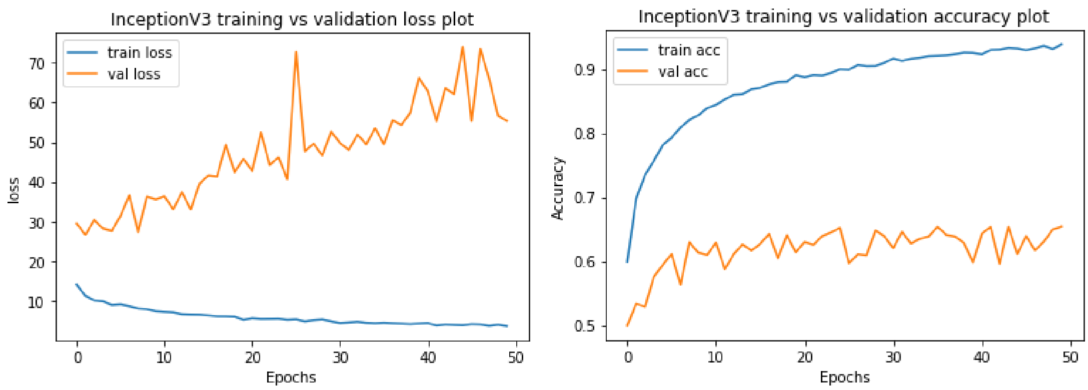

Figure-3: InceptionV3 accuracy and loss trend

There is a huge gap between training accuracy and validation accuracy. While the training accuracy gradually increases, the validation accuracy plateaus around 64%. It shows that the model is overfitting on training data and not able to generalize component features which describe the poor performance in validation accuracy. The training loss decreases but validation loss is increasing with each epoch.
The test accuracy is 52.10% for the InceptionV3 model.

5.2 EfficientNetB1

The following figures describe the accuracy and loss trend for EfficientNetB1

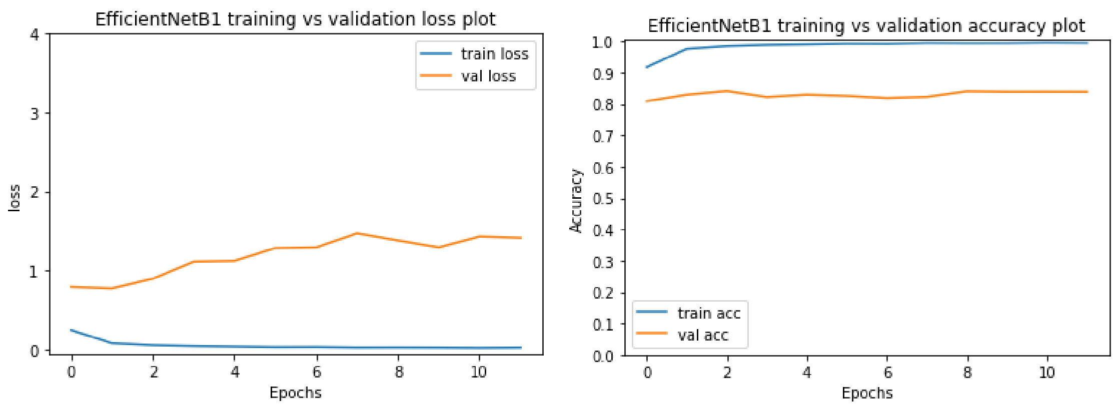

Figure-4: EfficientNetB1 accuracy and loss trend

This model quickly improves its accuracy with each epoch. The validation accuracy also improves quickly. The validation accuracy plateaus around 83% and training accuracy quickly moves to 99%. The loss trend shows that validation loss increases but plateaus around 1.3. This model provides 60.02% accuracy on the test dataset.

5.3 EfficientNetB2

The following figures describe the accuracy and loss trend for EfficientNetB2

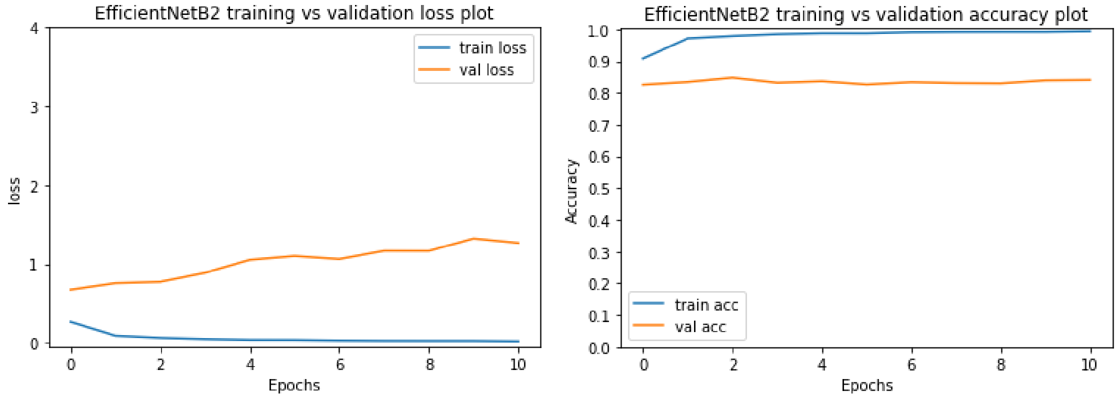

Figure-5: EfficientNetB2 accuracy and loss trend

Similar to EfficientNetB1, this model also quickly improves its accuracy with each epoch. The validation accuracy increases and plateaus around 83%. The training loss decreases quickly but the validation loss increases with each epoch. Due to the early stopping parameter, it stops after the 12th epoch. The test accuracy is lower than the test accuracy of EfficientNetB1. The test accuracy is 58.65%.

5.4 Xception

The following figures describe the accuracy and loss trend for Xception.

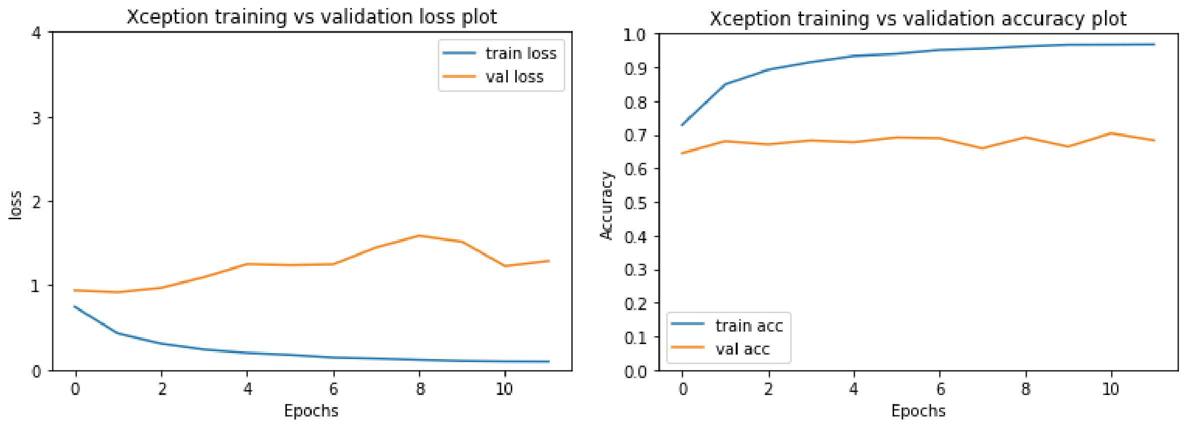

Figure-6: Xception accuracy and loss trend

The training and validation accuracy increase is slower than the previous three models. The Training accuracy reaches around 97% and validation accuracy does not go beyond 73%. It shows that there is no significant improvement in feature generalization over previous models. The training stops after the 13th epoch due to the early stop mechanism. While training loss decreases towards 0, the validations loss increases and plateaus around 1. This model has an F1-score of 57.00.

5.5 ResNet152V2

The following figures describe the accuracy and loss trend for ResNet152V2.

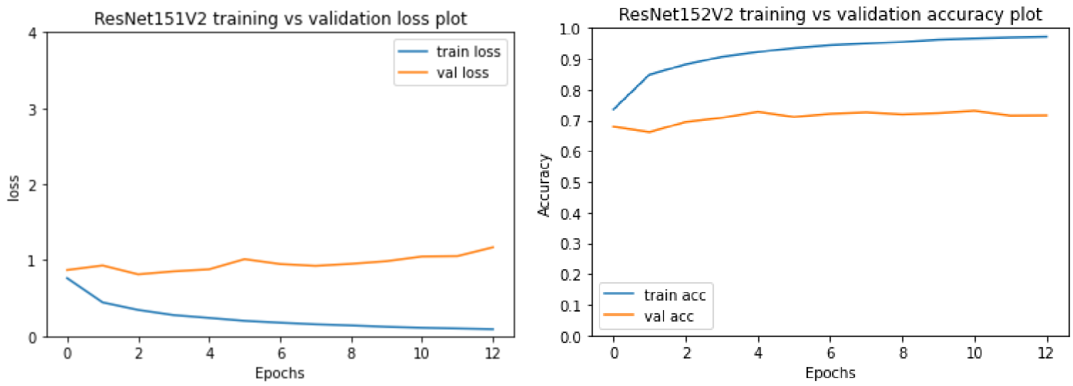

Figure-7: ResNet152V2 accuracy and loss trend

This model also does not perform better than EfficientNet models. Its training and validation accuracy increase at the slowest speed. The training accuracy reaches around 97% and validation accuracy reaches around 71%. There is a clear sign that validation loss is increasing with each epoch. It means the model is overfitting on training data and not generalizing well enough to provide good accuracy over unseen data. The F1-score for this model is 50.34.

5.6 Discussion

The following table shows the F1-score comparison for the five models.

Table-4: F1-Score comparison

InceptionV3	**52.10**
EfficientNetB1	**60.02**
EfficientNetB2	**58.65**
Xception	**57.00**
ResNet152V2	**50.34**

The comparison of the five models shows an interesting trend that the heavier and more complex models are not able to generalize better than simpler models. Among the five models, EfficientNetB1 has the highest accuracy rate of 60.02%. Both the EfficientNet models perform better than other models. ResNet152V2 has the maximum number of layers, yet its performance is the poorest among the models.

These results show that there has to be further refinement in hyperparameter selection and the dataset pre-processing needs further attention. The image size for the experiments is fixed at 150 pixels. Increasing the pixel size to 224 might improve the accuracy of the results further. However, it requires heavier hardware and GPU than what has been used in this research.

6 Conclusion and Future Work

This research focused on preparing a classification model which can aid in printed circuit board (PCB) component defect detection by accurately identifying electrical components in a

densely packed PCB. It takes into consideration real-world scenarios such as differences in illumination, image scale, and image variance. This provides a challenging scenario to have an optimized model which can generalize enough features under varying circumstances in order to get a model which can be deployed in production. Due to the smaller number of images, transfer learning models have been used in order to take advantage of their existing training on a large dataset. The five transfer learning models used in the research are InceptionV3, EfficientNetB1, EfficientNetB2, Xception and ResNet152V2.
From research, it is found that the simpler and smaller models perform better than more complex models and EfficientNetB1 has the best test accuracy of 60.02%.

Future Work: The highest accuracy achieved is not satisfactory as it achieves just above 60%. In order to improve model accuracy, further hyperparameter tuning and image pre-processing are required. Other latest transfer learning models can also be used in order to compare and improve model accuracy.

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8 References

Guerra, E. & Villalobos, J., 2001. A three-dimensional automated visual inspection system for SMT assembly. *Computers & Industrial Engineering,* Volume 40, pp. 175-190.

Hatcher, W. & Yu, W., 2018. A Survey of Deep Learning: Platforms, Applications and Emerging Research Trends. *IEEE,* Volume 6, pp. 24411-24432.

He, X., Wang, S., Tang, Z. & Wang, Y., 2019. *Computer-Aided Clinical Skin Disease Diagnosis Using CNN and Object Detection Models.* s.l., IEEE International Conference on Big Data (Big Data), pp. 4839-4844.

Lim, D., Kim, Y. & Park, T., 2019. SMD Classification for Automated Optical Inspection Machine Using Convolution Neural Network. *IEEE,* pp. 395-398.

Liu, X., Yu, W., Liang, F. & Griffith, D., 2021. Toward Deep Transfer Learning in Industrial Internet of Things. *IEEE,* 8(15), pp. 12163-12175.

Moganti, M. & Ercal, F., 1995. Automatic PCB inspection systems. *IEEE,* 14(3), pp. 6-10.

Rafiq, M., Agyeman, R. & Choi, G., 2020. Scene Classification for Sports Video Summarization Using Transfer Learning. *Sensors (Switzerland).*

Walkoli, D., Sali, V. & Patil, S., 2021. *Content-Based Image Retrieval using SIFT and CNN.* s.l., Asian Conference on Innovation in Technology (ASIANCON).

Wang, S., Xia, X., Ye, L. & Yang, B., 2020. Steel Surface Defect Detection Using Transfer Learning and Image Segmentation. *IEEE,* pp. 420-425.

Xie, F., Song, A. & Uitdenbogerd, A., 2013. Detecting PCB component placement defects by genetic programming. *IEEE,* pp. 1138-1145.

Ying, Z., Xuan, C., Zhai, Y. & Deng, W., 2020. Deep Transferred Atrous-Inception CNN for Small Samples SAR ATR. *Sensors (Switzerland).*

Zheng, X., Jia, R., Gong, L. & Zhang, G., 2020. Component identification and defect detection in transmission lines based on deep learning. *Journal of Intelligent and Fuzzy Systems,* pp. 1-12.