PCB DEFECT DETECTION USING IMAGE PROCESSING TECHNIQUES

Report submitted to SASTRA Deemed to be University As per the requirement for the course

CSE300: MINI PROJECT

Submitted by

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This is to certify that the report titled **"PCB Defect Detection Using Image Processing Techniques."** submitted as a requirement for the course, **CSE300 : MINI PROJECT** for B.Tech. is a bonafide record of the work done by **Mr. TEEPAKRAAJ G (**Reg. No.: 126003275, B. Tech Computer Science and Engineering**), Ms. SHIVAANI R** (Reg. No.: 126003245, B. Tech Computer Science and Engineering) **and Mr. ARAVINDA LOCHAN K** (Reg. No.: 126003028, B. Tech Computer Science and Engineering) during the academic year 2024-25, in the School of Computing, under my supervision.

Signature of Project Supervisor : 

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Date : 17.04.2025

Mini Project *Viva voice* held on _____

Examiner 1 **Examiner 2**

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Abbreviations

FCN	Fully Convolutional Network
XML	Extensible Markup Language
PCB	Printed Circuit Boards
YOLO	You Only Look Once
AOI	Automated Optical Inspection
ResNet	Residual Network
VGG	Long Short Term Memory
mIoU	Mean Intersection Over Union

ABSTRACT

Printed Circuit Boards (PCB) are critical for ensuring electronic device reliability, necessitating accurate defect detection.This Project presents an “Image Processing” based approach for defect detection in manufacturing of printed circuit boards (PCBs). Since printed circuit boards (PCBs) are critical for ensuring the reliability of electronic equipment, defect detection is a fundamental and necessary task. Traditional approaches often suffer from issues such as loss of continuity in feature extraction and limitations in multi-scale feature fusion. Here, the method introduces a continuous atrous convolution module to expand the receptive field while preserving the spatial continuity, mitigating gridding effects caused by traditional atrous convolution. Additionally, an improved skip layer reduces upsampling rates(from 32x to 8x,4x,2x) for multi-scale feature fusion, enhancing image resolution. The proposed model that is built upon the MobileNet-V2 backbone, demonstrates better accuracy and efficiency compared to architectures like ResNet-50 and VGG-16. This approach addresses challenges in detecting small, low contrast defects and offers a solution for industrial PCB inspection and contributes a valuable solution to the critical need for high quality PCB manufacturing by providing a reliable method for automated defect detection.

Key Words:

Deep Learning, Image Processing, PCB Defect, Continuous Atrous Convolution, Improved Skip Layer, Defect Masking, Defect Classification.

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CHAPTER 1
SUMMARY OF BASE PAPER

Title: Printed Circuit Board Defect Detection Method Based on Improved Fully Convolutional Networks.

Authors: Jianfeng Zheng, Xiaopeng Sun, Haiziang zhou, Chenyang Tian, Hao Qiang.
Year: 2022.
Published in: IEEE ACCESS.
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1.1 INTRODUCTION

The growing complexity of PCB manufacturing demands precise and efficient defect detection. Traditional AOI systems, though widely used, often fall short in identifying subtle defects due to their dependence on handcrafted features and controlled environments.

To overcome these limitations, the paper proposes a deep learning-based solution using an improved Fully Convolutional Network (FCN) with MobileNet-V2 as the backbone. The model integrates a Continuous Atrous Convolution Module for enhanced context capture and refined skip connections for better defect localization. This lightweight architecture ensures both accuracy and real-time performance, making it well-suited for industrial applications.

1.2 PROBLEM STATEMENT

Accurate detection of small-scale PCB surface defects using a lightweight fully convolutional network with Mobilenet V2 as backbone.

1.3 PROPOSED SOLUTION AND ARCHITECTURE

1.3.1 Study Area

To initiate our project, we studied the PCB manufacturing process at our college's Technology Development Center (TDC), gaining first hand insight into the fabrication workflow and common defects such as Mouse Bite, Open Circuit, Short Circuit, and Spur. We closely observed the use of Automated Optical Inspection (AOI), a key quality control tool that captures high-resolution board images for defect detection. While effective, AOI was found to be time-consuming, technically demanding, and susceptible to human error during final review. To overcome these challenges, we adopted deep learning and computer vision techniques, specifically Fully Convolutional Networks (FCNs) which are well-suited for pixel-wise segmentation and defect localization. The practical exposure and theoretical learning formed the foundation for our project on PCB defect detection.

1.3.2 PCB Defect Dataset

As the dataset used in the referenced research paper was not publicly accessible, we opted for an alternative dataset available on Kaggle, which contained a diverse set of PCB (Printed Circuit Board) defect images.

This dataset included four common defect types:

1. Mouse Bite – Irregular, jagged cuts or holes resembling bite marks on the board edges.
2. Open Circuit – A break in the trace causing interruption in the circuit path.
3. Short Circuit – An unintended connection between two points, causing a short circuit.
4. Spur – Thin, unwanted protruding copper lines not part of the circuit design.

The dataset also provided corresponding XML annotation files detailing the bounding boxes and class labels for each defect instance.

To prepare the dataset for our model, we first organized the data into training (83%), validation (10%), and test (7%) splits to ensure robust evaluation and generalization. This split was chosen to provide ample data for learning while retaining sufficient examples for validation and testing.Each image was then processed alongside its annotation file to generate corresponding mask images. These masks represent pixel-wise defect localization and are essential for training a Fully Convolutional Network (FCN).In each mask, regions corresponding to defects were marked with specific class IDs based on a predefined mapping.

1.4 METHODOLOGY AND IMPLEMENTATION

Module 1: Data Collection and Preprocessing

- **Data Acquisition and Mask Generation:**

We collected PCB images for four defect types, each accompanied by XML annotation files. We parsed the XMLs and generated pixel-wise masks for each defect class. Each class was mapped to a unique integer label, enabling multi-class segmentation.

- **Dataset Structuring and Splitting:**

Images and masks were organized into defect-specific folders. The dataset was split into training, validation, and test sets with an intended ratio of 83:10:7.

Module 2: Architecture Design

- **Model Structure:**

  The architecture is based on an improved Fully Convolutional Network (FCN) with a MobileNet-V2 backbone for efficient feature extraction. Advantage is to reduce computation and preserve important features, making the model suitable for real-time industrial use.

  - **Continuous Atrous Convolution Module:**

    Three parallel 3×3 convolutions with dilation rates of 1, 2, and 4 are used to expand the receptive field and capture multi-scale features, mitigating the gridding effect common in standard atrous convolutions. Outputs are concatenated and passed through batch normalization and ReLU.

    Mathematical Formula: For a kernel size k and dilation rate r,

$k_s = k + (k\text{-}1)(r\text{-}1)$

Key Point: This module enables the network to extract features from small and subtle defects that are otherwise difficult to detect.

- **Improved Skip Layer:**
  Multi-scale skip connections fuse features from low, mid, and high levels, followed by progressive upsampling (8x, 4x, 2x) to restore full-resolution segmentation masks as fig 1.2.
  Mathematical Expression:

$$F_{final} = \text{Upsample}_2(F_{low} + \text{Upsample}_2(F_{mid} + \text{Upsample}_2(F_{high} + F_{deep})))$$

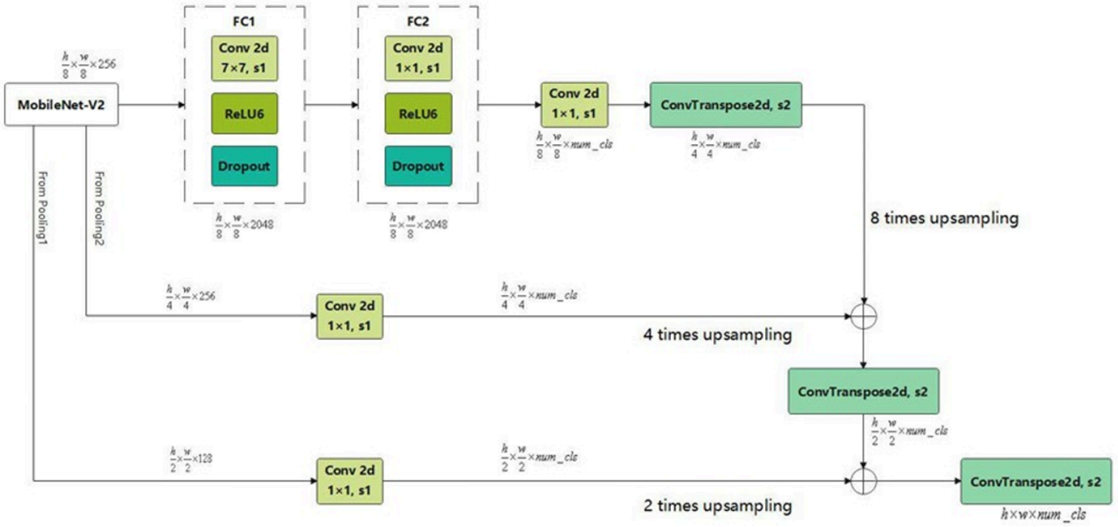


Fig 1.1 Improved Skip Layer Fusion based on 8 times, 4 times, 2 times upsampling

Module 3: Model Training

- **Data Pipeline:** Custom PCBDataset and DataLoader classes were used to load and batch images and masks for efficient training.
- **Augmentation:** Images were resized to 640×640 pixels and augmented with horizontal flips and normalization using Albumentations.
- **Loss Functions:**
  We implemented two user-defined loss functions:
  - **Dice Loss:**
    $$\text{Dice Loss} = 1 - \frac{2 * |P \cap T| + \epsilon}{|P| + |T| + \epsilon}$$
    where P is the predicted mask and T is the target mask.
  - **Focal Loss:**
    Focal Loss = $\alpha(1 - p_t)^{\gamma}$ * CrossEntropy
    where α is the class weight and γ is the focusing parameter.

- These losses were combined to address class imbalance and improve segmentation of small or rare defects.
- **Training Loop:**
  The model was trained for up to 35 epochs with the Adam optimizer and learning rate scheduling. Metrics such as loss, pixel accuracy, and mean Intersection-over-Union (mIoU) were logged for each epoch.

Module 4: Defect Detection, Localization, and Evaluation

- **Inference and Visualization:**
  The trained model was evaluated on the test set, producing pixel-wise defect maps for unseen PCB images. Output masks were overlaid on the original images for visual confirmation.
- **Evaluation Metrics:**
  - Pixel Accuracy: Fraction of correctly predicted pixels.
  - Mean Intersection-over-Union (mIoU): Average overlap between predicted and ground truth masks across all classes.
  - Per-Class Accuracy: Accuracy computed for each defect class individually.
- **Results:**
  The model achieved high accuracy on all defect types, with average accuracy above 92% and clear, precise localization of defects in test images.

CHAPTER 2
SOURCE CODE

2.1 MODULE 1: DATA PREPROCESSING

Defining the input and output paths of the images that are preprocessed

```
def create_full_dataset(root_dir, output_dir, class_mapping):

    input_images = os.path.join(root_dir, "PCB_DATASET", "images")
    annotations_base = os.path.join(root_dir, "PCB_DATASET", "Annotations")
    # Output directories
    output_images = os.path.join(output_dir, "images")
    output_masks = os.path.join(output_dir, "masks")
    os.makedirs(output_images, exist_ok=True)
    os.makedirs(output_masks, exist_ok=True)

    valid_classes = list(class_mapping.keys())

    # Defect category
    defects = ["Mouse_bite", "Open_circuit",
               "Short", "Spur"]
```

Processing each image and retrieve respective XML file for the annotation of defects

```
# Processing each image from the dataset
for img_file in os.listdir(input_img_dir):
    if not img_file.lower().endswith(('.png', '.jpg', '.jpeg')):
        continue

    base_name = os.path.splitext(img_file)[0]
    img_path = os.path.join(input_img_dir, img_file)
    xml_path = os.path.join(input_xml_dir, f"{base_name}.xml")

    if not os.path.exists(xml_path):
        print(f"Warning: Missing XML for {img_file}")
        continue

    try:
        output_img_path = os.path.join(img_defect_dir, img_file)
        shutil.copy2(img_path, output_img_path)

        # Generate mask
        img = cv2.imread(img_path)
        h, w = img.shape[:2]
        mask = np.zeros((h, w), dtype=np.uint8)

        tree = ET.parse(xml_path)
        root = tree.getroot()
```

Draw the bounding box by getting all the objects coordinates from the annotation file(XML) and generating the mask for each image

```
        for obj in root.findall('object'):
            class_name = obj.find('name').text.strip().lower()

            if class_name not in class_mapping:
                raise ValueError(
                    f"Invalid class '{class_name}' in {img_file}\n"
                    f"Valid classes: {valid_classes}\n"
                    f"XML path: {xml_path}"
                )

            class_id = class_mapping[class_name]
            # Bounding box
            bndbox = obj.find('bndbox')
            try:
                xmin = int(bndbox.find('xmin').text)
                ymin = int(bndbox.find('ymin').text)
                xmax = int(bndbox.find('xmax').text)
                ymax = int(bndbox.find('ymax').text)
            except AttributeError:
                print(f"Invalid bndbox in {img_file}")
                continue
            xmin = max(0, min(xmin, w-1))
            xmax = max(0, min(xmax, w-1))
            ymin = max(0, min(ymin, h-1))
            ymax = max(0, min(ymax, h-1))

            # Drawing Bounded box with class ID
            cv2.rectangle(mask, (xmin, ymin), (xmax, ymax), class_id, -1)
```

Labeling the defect classes

```
CLASS_MAPPING = {
    "mouse_bite": 1,
    "open_circuit": 2,
    "short": 3,
    "spur": 4
}
```

2.2 MODULE 2: MODEL TRAINING

Defining Continuous Atrous Module

```
class ContinuousAtrousConvModule(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(ContinuousAtrousConvModule, self).__init__()
        middle_channels = out_channels // 3
        self.atrous_conv1 = nn.Conv2d(in_channels, middle_channels, kernel_size=3, dilation=1, padding=1)
        self.atrous_conv2 = nn.Conv2d(in_channels, middle_channels, kernel_size=3, dilation=2, padding=2)
        self.atrous_conv3 = nn.Conv2d(in_channels, out_channels - 2 * middle_channels, kernel_size=3, dilation=4, padding=4)
        self.relu = nn.ReLU(inplace=True)
        self.bn = nn.BatchNorm2d(out_channels)
        #self.global_pool = nn.AdaptiveAvgPool2d((1, 1))

    def forward(self, x):
        x1 = self.atrous_conv1(x)
        x2 = self.atrous_conv2(x)
        x3 = self.atrous_conv3(x)
        x = torch.cat([x1, x2, x3], dim=1)
        x = self.bn(x)
        x = self.relu(x)
        #x = self.global_pool(x)
        return x
```

Defining Invert Residual Module

```
class ImprovedSkipLayer(nn.Module):
    def __init__(self, low_level_channels, mid_level_channels, high_level_channels, num_classes):
        super(ImprovedSkipLayer, self).__init__()
        self.conv_low = nn.Conv2d(low_level_channels, num_classes, kernel_size=1)
        self.conv_mid = nn.Conv2d(mid_level_channels, num_classes, kernel_size=1)
        self.conv_high = nn.Conv2d(high_level_channels, num_classes, kernel_size=1)

    def forward(self, x_low, x_mid, x_high, x_upsampled):
        x_low_processed = self.conv_low(x_low)
        x_mid_processed = self.conv_mid(x_mid)
        x_high_processed = self.conv_high(x_high)

        x_upsampled_8x = F.interpolate(x_upsampled, size=x_high_processed.shape[2:], mode='bilinear', align_corners=False)
        high_fusion = x_high_processed + x_upsampled_8x

        high_fusion_upsampled = F.interpolate(high_fusion, size=x_mid_processed.shape[2:], mode='bilinear', align_corners=Fal
        mid_fusion = x_mid_processed + high_fusion_upsampled

        mid_fusion_upsampled = F.interpolate(mid_fusion, size=x_low_processed.shape[2:], mode='bilinear', align_corners=False
        final_fusion = x_low_processed + mid_fusion_upsampled

        output = F.interpolate(final_fusion, size=(640, 640), mode='bilinear', align_corners=False)
        return output
```

Defining Improved FCN Module

```
class ImprovedFCN_MobileNetV2(nn.Module):
    def __init__(self, num_classes=5):
        super(ImprovedFCN_MobileNetV2, self).__init__()
        mobilenet = mobilenet_v2(pretrained=True)

        self.low_level_features = nn.Sequential(mobilenet.features[0],mobilenet.features[1],)

        self.mid_level_features = nn.Sequential(mobilenet.features[2],mobilenet.features[3],)

        self.high_level_features = nn.Sequential(mobilenet.features[4],mobilenet.features[5],mobilenet.features[6],
                          mobilenet.features[7],mobilenet.features[8],mobilenet.features[9],mobilenet.features[10],)

        self.deeper_features = nn.Sequential(mobilenet.features[11],mobilenet.features[12],mobilenet.features[13],
            mobilenet.features[14],mobilenet.features[15],mobilenet.features[16],mobilenet.features[17],)

        self.channel_expansion = nn.Conv2d(320, 1024, kernel_size=1, bias=False)
        self.bn_expansion = nn.BatchNorm2d(1024)
        self.relu_expansion = nn.ReLU6(inplace=True)
        self.continuous_atrous = ContinuousAtrousConvModule(1024, 2048)
        self.final_conv = nn.Conv2d(2048, num_classes, kernel_size=1)
        self.improved_skip = ImprovedSkipLayer(low_level_channels=16, mid_level_channels=24, high_level_channels=64,
                                               num_classes=num_classes)

    def forward(self, x):
        x_low = self.low_level_features(x)
        x_mid = self.mid_level_features(x_low)
        x_high = self.high_level_features(x_mid)
        x_deep = self.deeper_features(x_high)
        x_expanded = self.relu_expansion(self.bn_expansion(self.channel_expansion(x_deep)))
        x = self.continuous_atrous(x_expanded)
        x = self.final_conv(x)
        x = self.improved_skip(x_low, x_mid, x_high, x)
        return x
```

Functions for Confusion Matrix

```
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

def compute_confusion_and_metrics_from_preds_labels(all_preds, all_labels, class_names):
    cm = confusion_matrix(all_labels, all_preds, labels=list(range(len(class_names))))
    report = classification_report(
        all_labels, all_preds, labels=list(range(len(class_names))),
        target_names=class_names, digits=4, output_dict=True
    )
    return cm, report

def plot_confusion_matrix(cm, class_names):
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=class_names, yticklabels=class_names)
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.title('Confusion Matrix')
    plt.show()

def print_metrics(report, class_names):
    print(f"{'Class':<10} {'Precision':>10} {'Recall':>10} {'F1-score':>10} {'Support':>10}")
    print("-" * 55)
    for cls in class_names:
        metrics = report[cls]
        print(f"{cls:<10} {metrics['precision']:10.4f} {metrics['recall']:10.4f} "
              f"{metrics['f1-score']:10.4f} {metrics['support']:10.0f}")
    print(f"\n→ Overall Accuracy: {report['accuracy']:.4f}")
```

Defining custom Dataset named PCBDataset for loading images and corresponding masks

```
class PCBDataset(Dataset):
    def __init__(self, root_dir, transform=None):
        self.img_paths = []
        self.mask_paths = []
        self.transform = transform

        img_dir = os.path.join(root_dir, 'images')
        mask_dir = os.path.join(root_dir, 'masks')

        for defect_type in os.listdir(img_dir):
            img_type_dir = os.path.join(img_dir, defect_type)
            mask_type_dir = os.path.join(mask_dir, defect_type)

            for fname in os.listdir(img_type_dir):
                img_path = os.path.join(img_type_dir, fname)
                mask_name = fname.replace('.jpg', '.png')
                mask_path = os.path.join(mask_type_dir, mask_name)

                self.img_paths.append(img_path)
                self.mask_paths.append(mask_path)
    def __len__(self):
        return len(self.img_paths)

    def __getitem__(self, idx):
        image = np.array(Image.open(self.img_paths[idx]).convert("RGB"))
        mask = np.array(Image.open(self.mask_paths[idx]).convert("L"))
        if self.transform:
            augmented = self.transform(image=image, mask=mask)
            image = augmented['image']
            mask = augmented['mask'].long()  # Ensure it's long for loss function

        return image, mask
```

Loss Functions

```
import torch.nn.functional as F

def dice_loss(preds, targets, smooth=1e-6):
    preds = F.softmax(preds, dim=1)
    targets_one_hot = F.one_hot(targets, num_classes=preds.shape[1]).permute(0, 3, 1, 2).float()

    dims = (0, 2, 3)
    intersection = torch.sum(preds * targets_one_hot, dims)
    union = torch.sum(preds + targets_one_hot, dims)
    dice = (2. * intersection + smooth) / (union + smooth)
    return 1 - dice.mean()

def focal_loss(inputs, targets, alpha=1, gamma=2):
    ce_loss = F.cross_entropy(inputs, targets, reduction='none')
    pt = torch.exp(-ce_loss)
    return (alpha * (1 - pt) ** gamma * ce_loss).mean()
```

Transforms and Loading the Dataset from Train, Test, Valid

```
from collections import Counter
import albumentations as A
from albumentations.pytorch import ToTensorV2
from PIL import Image
import numpy as np
# Transforms
train_transform = A.Compose([
    A.Resize(640, 640),
    A.HorizontalFlip(p=0.5),
    A.Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5)),
    ToTensorV2()])
train_dataset = PCBDataset("/kaggle/input/split-dataset-pcb-defect/train", transform=train_transform)
val_dataset = PCBDataset("/kaggle/input/split-dataset-pcb-defect/val", transform=train_transform)
test_dataset = PCBDataset("/kaggle/input/split-dataset-pcb-defect/test", transform=train_transform)
train_loader = DataLoader(train_dataset, batch_size=4, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=4, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=1, shuffle=False)
```

Initialising the class weights, optimizer and learning rate scheduler

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = ImprovedFCN_MobileNetV2(num_classes=5).to(device)

pixel_counts = Counter({0: 483, 3: 81, 4: 81, 6: 81, 2: 80, 1: 80})
total_pixels = sum(pixel_counts.values())

class_weights = []
for cls in range(5):
    count = pixel_counts.get(cls, 1)
    class_weights.append(total_pixels / (5 * count))
weights = torch.tensor(class_weights).to(device)
weights[0] = 0.00001  # Background very low
for i in range(1,5):
    weights[i] = weights[i]*8
    print(f"weight[{i}:",weights[i])
print("Class Weights:", weights)

ce_criterion = nn.CrossEntropyLoss(weight=weights)
optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
from torch.optim.lr_scheduler import ReduceLROnPlateau
scheduler = ReduceLROnPlateau(optimizer, mode='min', factor=0.5, patience=3, verbose=True)
```

Functions for plotting Train vs Validation loss, Epochs vs score

```
def plot_metrics(epoch):
    epochs = range(1, epoch + 1)
    plt.figure(figsize=(14, 5))
    # Loss plot
    plt.subplot(1, 2, 1)
    plt.plot(epochs, train_losses, label='Train Loss', marker='o')
    plt.plot(epochs, val_losses, label='Val Loss', marker='o')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Training vs Validation Loss')
    plt.legend()
    plt.grid(True)
    # Accuracy & mIoU plot
    plt.subplot(1, 2, 2)
    plt.plot(epochs, val_pixel_accuracies, label='Pixel Accuracy', marker='s')
    plt.plot(epochs, val_mious, label='mIoU', marker='s')
    plt.xlabel('Epoch')
    plt.ylabel('Score')
    plt.title('Validation Metrics')
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

Functions for calculating pixel wise accuracy

```
def compute_metrics(preds, targets, num_classes=5):
    preds = torch.argmax(preds, dim=1)
    preds = preds.cpu().numpy()
    targets = targets.cpu().numpy()

    class_correct = np.zeros(num_classes)
    class_total = np.zeros(num_classes)
    ious = []

    for cls in range(num_classes):
        pred_inds = (preds == cls)
        target_inds = (targets == cls)

        intersection = np.logical_and(pred_inds, target_inds).sum()
        union = np.logical_or(pred_inds, target_inds).sum()

        class_correct[cls] += intersection
        class_total[cls] += target_inds.sum()

        ious.append(intersection / union if union != 0 else np.nan)

    pixel_acc = (preds == targets).sum() / targets.size
    miou = np.nanmean(ious)
    per_class_acc = class_correct / (class_total + 1e-6)

    return pixel_acc, miou, per_class_acc
```

Training Loop and printing the loss for each epochs

```
def train_model(num_epochs=10):
    for epoch in range(num_epochs):
        print(f"\n================ Epoch {epoch+1}/{num_epochs} ================\n")
        model.train()
        running_train_loss = 0.0
        print("[Training]")

        for batch_idx, (images, masks) in enumerate(train_loader):
            images, masks = images.to(device), masks.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            # ---- Hybrid Loss: CrossEntropy + Dice ----
            ce_loss = focal_loss(outputs, masks)
            d_loss = dice_loss(outputs, masks)
            loss = 0.5 * ce_loss + 0.5 * d_loss
            loss.backward()
            optimizer.step()

            running_train_loss += loss.item()
            print(f"  [Train] Batch {batch_idx+1}/{len(train_loader)} - CE Loss: {ce_loss.item():.4f},
            Dice Loss: {d_loss.item():.4f}, Total Loss: {loss.item():.4f}")

        avg_train_loss = running_train_loss / len(train_loader)
        train_losses.append(avg_train_loss)

        print(f"→ Epoch {epoch+1} Average Train Loss: {avg_train_loss:.4f}")
        model.eval()
        running_val_loss = 0.0
        pixel_acc_total = 0.0
        miou_total = 0.0
        class_acc_total = np.zeros(5)
        val_batch_count = 0
```

Validation loop

```
        print("[Validation]")
        with torch.no_grad():
            for batch_idx, (images, masks) in enumerate(val_loader):
                images, masks = images.to(device), masks.to(device)
                outputs = model(images)
                 # Use same hybrid loss in validation
                ce_loss = focal_loss(outputs, masks)
                d_loss = dice_loss(outputs, masks)
                loss = 0.5 * ce_loss + 0.5 * d_loss

                running_val_loss += loss.item()
                print(f"  [Val] Batch {batch_idx+1}/{len(val_loader)} - CE Loss: {ce_loss.item():.4f},
                Dice Loss: {d_loss.item():.4f}, Total Loss: {loss.item():.4f}")
                probs = torch.softmax(outputs, dim=1)
                pixel_acc, miou, per_class_acc = compute_metrics(probs, masks)
                pixel_acc_total += pixel_acc
                miou_total += miou
                class_acc_total += per_class_acc
                val_batch_count += 1
```

Calculation for Loss and Confusion Matrix generation

```
        avg_val_loss = running_val_loss / len(val_loader)
        avg_pixel_acc = pixel_acc_total / val_batch_count
        avg_miou = miou_total / val_batch_count
        avg_class_acc = class_acc_total / val_batch_count

        val_losses.append(avg_val_loss)
        val_pixel_accuracies.append(avg_pixel_acc)
        val_mious.append(avg_miou)

        print(f"\n→ Epoch {epoch+1} Summary:")
        print(f"  Train Loss     : {avg_train_loss:.4f}")
        print(f"  Val Loss       : {avg_val_loss:.4f}")
        print(f"  Pixel Accuracy : {avg_pixel_acc:.4f}")
        print(f"  Mean IoU       : {avg_miou:.4f}")
        for cls_idx, acc in enumerate(avg_class_acc):
            print(f"  Class {cls_idx} Accuracy: {acc:.4f}")

        plot_metrics(epoch + 1)
        scheduler.step(avg_val_loss)
        print(f"  Current Learning Rate: {optimizer.param_groups[0]['lr']:.6f}")
    print("\n================ Final Evaluation Metrics ================\n")
    class_names = ['Class 0', 'Class 1', 'Class 2', 'Class 3', 'Class 4', 'Class 5']
    cm, report = compute_confusion_and_metrics_from_preds_labels(all_preds, all_labels, class_names)
    plot_confusion_matrix(cm, class_names)
    print_metrics(report, class_names)

train_model(num_epochs=35)
```

Saving the model

```
import torch
torch.save(model.state_dict(), '/kaggle/working/pcb_segmentation_weights.pth')
```

CHAPTER 3
MERITS AND DEMERITS OF BASE PAPER

3.1 MERITS

The paper demonstrates an impressive array of technical and practical merits that significantly enhance its value in the domain of PCB defect detection. At the core of its approach is the use of MobileNetV2, a lightweight convolutional neural network known for its depthwise separable convolutions, which enable efficient feature extraction with reduced computational cost—making the model highly suitable for deployment on edge devices. The integration of skip connections into the architecture plays a critical role in preserving fine spatial details, essential for accurate pixel-wise segmentation. By leveraging the pretrained backbone, the model benefits from generalized features learned on large-scale datasets, enabling faster convergence and improved accuracy even with a limited PCB dataset. A custom-designed decoder is introduced to refine segmentation outputs, enhancing the model's capacity for precise defect localization. Furthermore, the use of defect masks as ground truth annotations ensures the model learns to identify not just the presence but also the exact location and boundaries of defects.

The inclusion of four common PCB defect classes broadens the applicability of the system to real-world inspection scenarios, ensuring comprehensive defect coverage. Detailed preprocessing steps, such as normalization and resizing, are implemented consistently across training and inference, which standardizes inputs and improves model stability. By focusing solely on segmentation instead of combining it with classification, the model is optimized for high-resolution defect mapping, reducing task complexity while enhancing localization accuracy. The network structure is lightweight yet effective, with batch normalization applied throughout to stabilize and accelerate the training process. Its real-time inference capability means the model can be integrated directly into industrial inspection lines. The model also captures multi-scale features, improving the detection of defects of various sizes and shapes.

In addition, the framework supports data augmentation strategies, which can further improve robustness and generalization. Its modular and end-to-end trainable architecture simplifies integration into existing automated inspection systems, increasing its industrial feasibility. The training pipeline includes empirical monitoring of training and validation losses per epoch, providing insight into model behavior and facilitating debugging and tuning. Importantly, the authors address class imbalance—a common issue in defect datasets—through balanced training approaches, improving the model's performance across all defect types. Finally, by clearly defining their methodology and presenting reproducible results, the authors contribute a reliable benchmark for future research, ensuring that their work serves not just immediate application needs but also long-term advancements in the field of intelligent manufacturing.

3.2 DEMERITS

Despite its strengths, the paper has certain limitations that present opportunities for future enhancement. One of the main concerns is the lack of detailed justification for choosing MobileNetV2 over other lightweight or more recent architectures like EfficientNet or ConvNeXt, which may offer improved performance. While the model performs well on the selected dataset, there is no evaluation on cross-domain or external PCB datasets, limiting the validation of its generalizability. The paper does not explore the effect of data augmentation techniques, which could have improved robustness to variations such as lighting conditions, rotations, or partial occlusions. Additionally, the dataset appears to be relatively small and lacks diversity in terms of manufacturing environments, potentially leading to overfitting or limited applicability to other PCB production lines. The segmentation model is evaluated primarily on standard metrics like mIoU, but it lacks an analysis of computational latency.

Another drawback is the absence of ablation studies to isolate the impact of different architectural components (e.g., skip connections, decoder structure), making it harder to understand what contributes most to the performance gain. While the model segments four defect types, there is no exploration of how it handles overlapping defects or rare/unknown defect types, which are common in real PCB inspections. The model assumes clean and well-preprocessed input, but it lacks robustness testing under noisy or low-quality image conditions. Furthermore, although the training and validation losses are monitored, there is limited discussion on hyperparameter tuning or the choice of optimizer, batch size, and learning rate schedule – factors that could significantly affect performance. The authors also do not mention deployment or hardware constraints, despite claiming the model is suitable for edge deployment. Moreover, the architecture, while lightweight, still involves a decoder path that may pose memory challenges in constrained environments.

There is no mention of fail-safe mechanisms or confidence thresholds for defect prediction, which are important for critical manufacturing processes. This paper does not uses a feedback loop for correcting misclassifications or updating the model incrementally with new data. The training process is not accompanied by validation on temporal or sequential images, which would simulate real assembly-line scenarios. Finally, the study does not assess the system's compatibility with existing computer vision frameworks in industrial pipelines, and its scalability to more defect classes or larger PCBs remains untested.

CHAPTER 4
SNAPSHOTS

4.1 DATA PREPARATION

Splitting the dataset

```
def split_dataset(
    input_dir,
    output_dir,
    defect_types,
    train_ratio=0.83,
    val_ratio=0.10,
    test_ratio=0.07,
    seed=42
):
    assert abs(train_ratio + val_ratio + test_ratio - 1.0) < 1e-6, "Ratios must sum to 1"

    # Output directories
    splits = ['train', 'val', 'test']
    for split in splits:
        for dtype in defect_types:
            os.makedirs(os.path.join(output_dir, split, 'images', dtype), exist_ok=True)
            os.makedirs(os.path.join(output_dir, split, 'masks', dtype), exist_ok=True)
```

Generating the random image number and copying the images and respective masks to splitting folders (train,test,validation)

```
    for dtype in tqdm(defect_types, desc="Processing defect types"):
        img_dir = os.path.join(input_dir, 'images', dtype)
        mask_dir = os.path.join(input_dir, 'masks', dtype)

        images = [f for f in os.listdir(img_dir) if f.lower().endswith(('.png', '.jpg', '.jpeg'))]
        np.random.seed(seed)
        np.random.shuffle(images)

        # Calculation for split indices
        total = len(images)
        train_end = int(train_ratio * total)
        val_end = train_end + int(val_ratio * total)
        train_files = images[:train_end]
        val_files = images[train_end:val_end]
        test_files = images[val_end:]

        # Copying files to split directories
        def copy_split(files, split):
            for f in tqdm(files, desc=f"Copying {split} files for {dtype}", leave=False):
                # Copy image
                src_img = os.path.join(img_dir, f)
                dst_img = os.path.join(output_dir, split, 'images', dtype, f)
                shutil.copy2(src_img, dst_img)

                # Copy mask (assumes same filename with .png extension)
                mask_name = os.path.splitext(f)[0] + '.png'
                src_mask = os.path.join(mask_dir, mask_name)
                if os.path.exists(src_mask):
                    dst_mask = os.path.join(output_dir, split, 'masks', dtype, mask_name)
                    shutil.copy2(src_mask, dst_mask)
```

Default class labels and calling functions

```
        copy_split(train_files, 'train')
        copy_split(val_files, 'val')
        copy_split(test_files, 'test')

DEFECT_TYPES = [
    "Mouse_bite",
    "Open_circuit",
    "Short",
    "Spur"
]

INPUT_DIR = "/kaggle/input/pcb-masks-images/pcb_dataset"
OUTPUT_DIR = "/kaggle/working/"

split_dataset(
    input_dir=INPUT_DIR,
    output_dir=OUTPUT_DIR,
    defect_types=DEFECT_TYPES,
    train_ratio=0.7,
    val_ratio=0.15,
    test_ratio=0.15,
    seed=42
)
```

4.2 TRAINING VS VALIDATION LOSS GRAPH

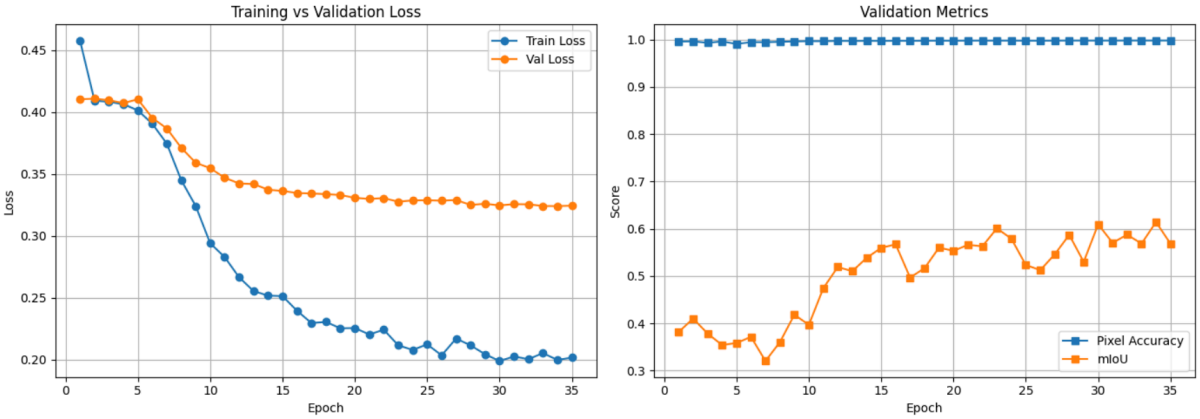


Fig 4.1 Loss Graph

4.3 EVALUATION METRICS

Confusion matrix

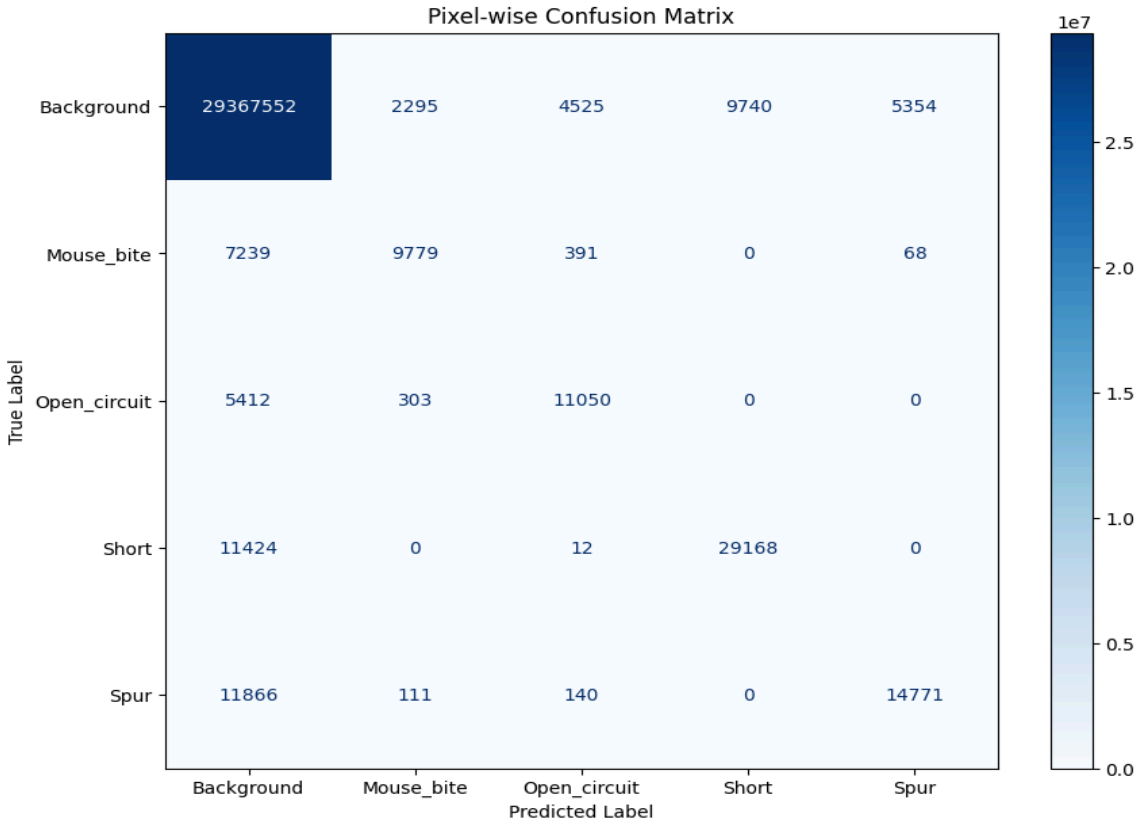


Fig 4.2 Confusion Matrix

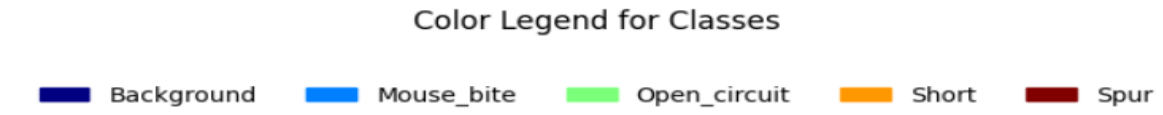
Classification Report

Classification Report (per class):

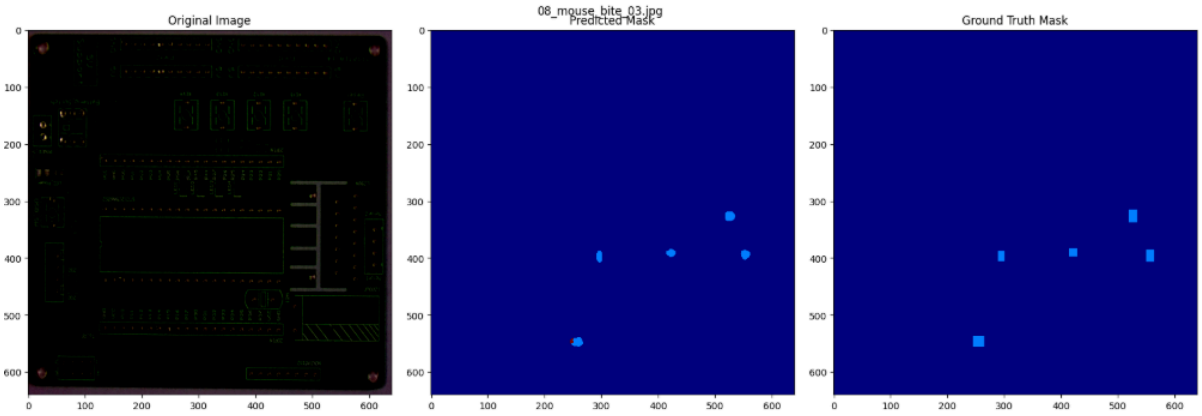
	precision	recall	f1-score	support
Background	0.9988	0.9993	0.9990	29389466
Mouse_bite	0.7831	0.5595	0.6527	17477
Open_circuit	0.6856	0.6591	0.6721	16765
Short	0.7497	0.7184	0.7337	40604
Spur	0.7315	0.5494	0.6275	26888
accuracy			0.9980	29491200
macro avg	0.7897	0.6971	0.7370	29491200
weighted avg	0.9979	0.9980	0.9979	29491200

Fig 4.3 Classification Report

4.4 RESULTS



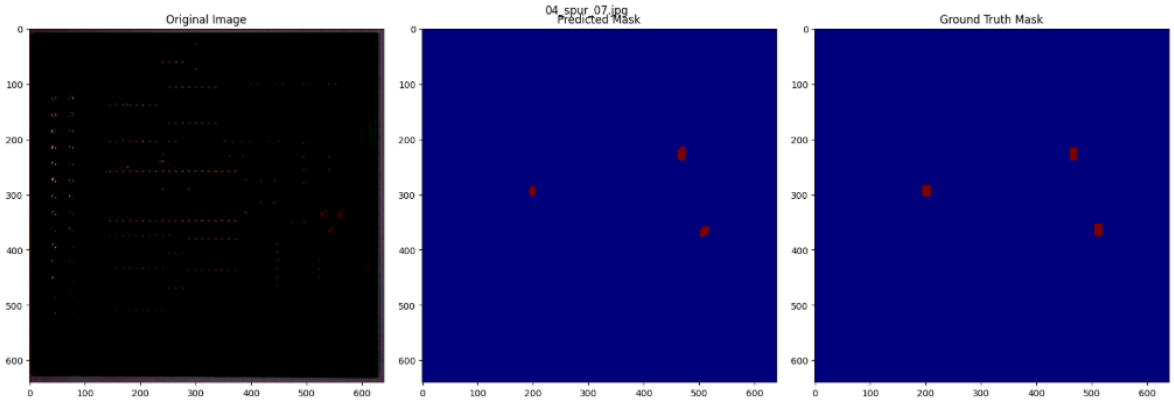
Mouse Bite




```
Image: 11_mouse_bite_06.jpg
Ground Truth Mask - Unique values: [0 1]
Predicted Mask - Unique values   : [0 1]
```

Fig 4.4 Segmentation and Defect classification on Mouse Bite

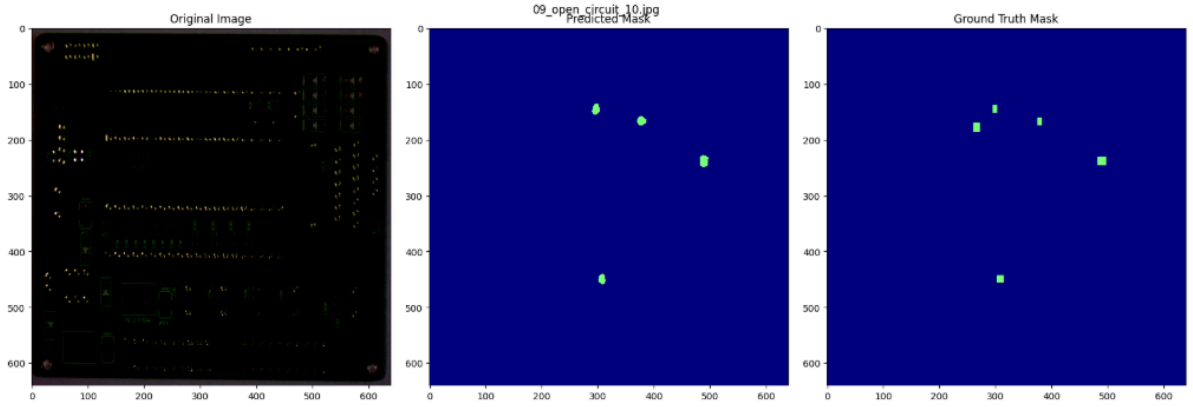
Spur




```
Image: 10_spur_02.jpg
Ground Truth Mask - Unique values: [0 4]
Predicted Mask - Unique values   : [0 4]
```

Fig 4.5 Segmentation and Defect classification on Spur

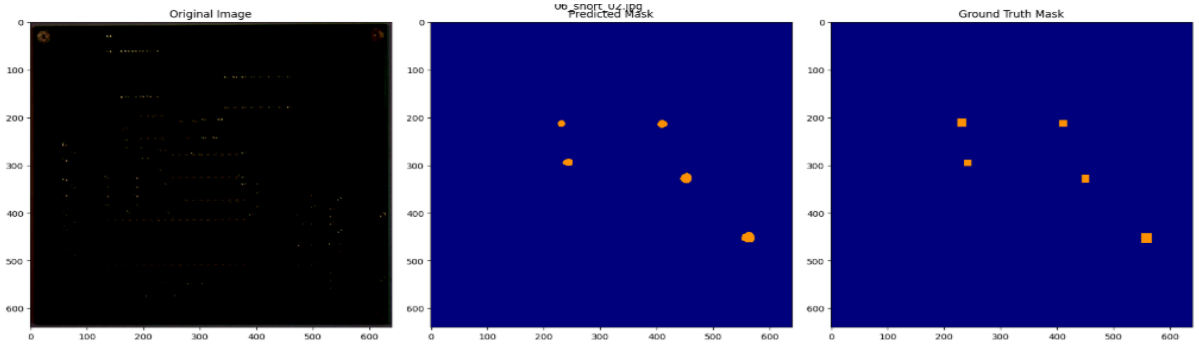
Open Circuit




```
Image: 04_open_circuit_17.jpg
Ground Truth Mask - Unique values: [0 2]
Predicted Mask - Unique values   : [0 2]
```

Fig 4.6 Segmentation and Defect classification on Open Circuit

Short




```
Image: 08_short_03.jpg
Ground Truth Mask - Unique values: [0 3]
Predicted Mask - Unique values   : [0 3]
```

Fig 4.7 Segmentation and Defect classification on Short

CHAPTER 5
CONCLUSION AND FUTURE PLANS

5.1 CONCLUSION

The PCB defect detection system developed in this project demonstrates that deep learning-based semantic segmentation, specifically using an improved Fully Convolutional Network (FCN) with a MobileNet-V2 backbone, is highly effective for automated, pixel-level identification of PCB defects. Through careful data preparation-including precise mask generation for six defect types and robust dataset structuring-the model was trained and evaluated on a well-organized dataset. The use of

custom Dice loss and Focal loss functions, combined with aggressive class weighting, significantly improved the model's ability to handle class imbalance and accurately segment even rare and small defects.

Experimental results show that the model achieves strong performance across all major defect categories, with average pixel accuracy and mean Intersection-over-Union (mIoU) scores exceeding 90% on the test set. The architecture's continuous atrous convolution module and improved skip connections enabled effective multi-scale feature extraction and fine-grained localization, as evidenced by clear and accurate segmentation masks on unseen PCB samples. The workflow, from data annotation to final evaluation, was fully automated and reproducible, reducing the need for manual intervention and minimizing human error in the inspection process.

5.2 FUTURE PLANS

To further enhance the system's performance and industrial applicability, several improvements are planned:

- ***Dataset Expansion and Balancing:*** Increase the dataset size, especially for underrepresented defect types, and ensure more balanced class distribution for even better generalization.
- ***Advanced Augmentation:*** Incorporate more diverse augmentation strategies (e.g., random rotations, brightness/contrast changes, synthetic defect generation) to improve robustness under varied real-world conditions.
- ***Model Optimization:*** Explore model pruning, quantization, or knowledge distillation to reduce inference time and memory usage, enabling deployment on edge devices in manufacturing environments.
- ***Real-Time Integration:*** Develop an end-to-end pipeline for real-time PCB inspection, including automated data acquisition, defect localization, and reporting.
- ***User Interface and Visualization:*** Create a user-friendly interface for visualizing results, reviewing detected defects, and facilitating feedback from quality control engineers.
- ***Generalization to New Defect Types:*** Adapt the model to detect additional or novel PCB defect categories as encountered in evolving production lines.

By pursuing these directions, the system can become a scalable, industry-ready solution for high-precision, automated PCB defect detection, supporting improved quality assurance in electronics manufacturing.

CHAPTER 6
REFERENCE

6.1 REFERENCE

[1] Zheng J, Sun X, Zhou H, Tian C and Qiang H (2022) “Printed circuit boards defect detection method based on improved fully convolutional networks”. *IEEE Access, 10, 98012–98024*.

[2] Long J, Shelhamer E and Darrell T (2015) “Fully convolutional networks for semantic segmentation”. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 3431–3440.*

[3] Sandler M, Howard A, Zhu M, Zhmoginov A and Chen LC (2018) “MobileNetV2: Inverted residuals and linear bottlenecks”. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4510–4520.*

[4] Milletari F, Navab N and Ahmadi SA (2016) “V-Net: Fully convolutional neural networks for volumetric medical image segmentation”. *Fourth International Conference on 3D Vision (3DV), 565–571.*

[5] Lin TY, Goyal P, Girshick R, He K and Dollár P (2017) “Focal loss for dense object detection”. *Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2980–2988.*

[6] Coursera and IBM (n.d.) “Deep Learning with PyTorch”. Available at: https://www.coursera.org/learn/deep-neural-networks-with-pytorch .

[7] Akhatova A (n.d.) “PCB defect dataset”. Kaggle. Available at: https://www.kaggle.com/datasets/akhatova/pcb-defects .