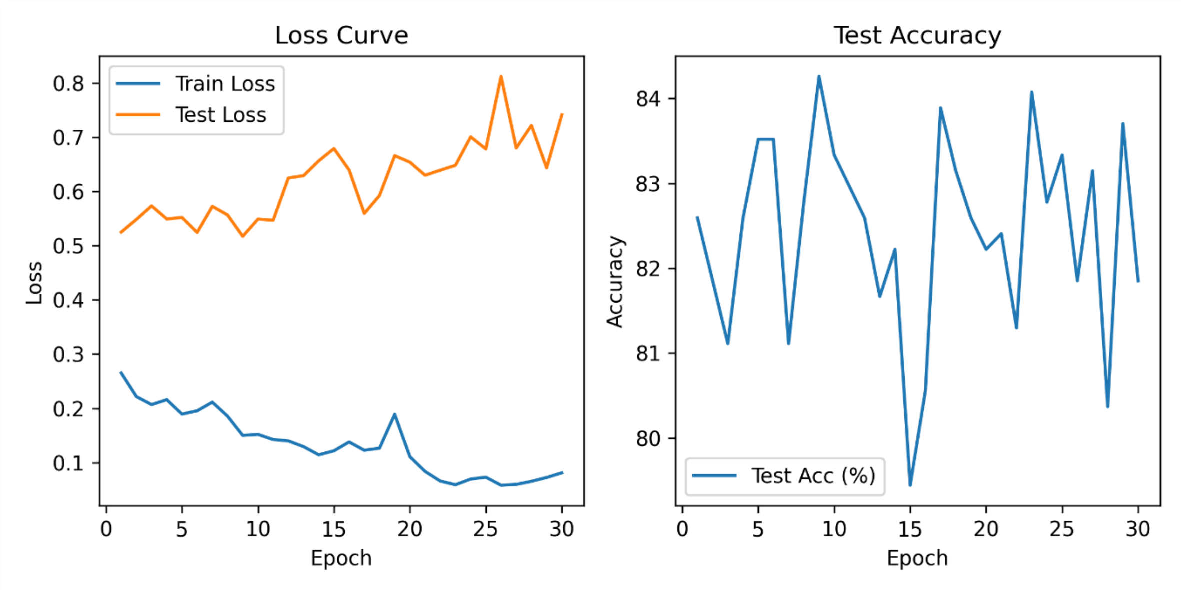
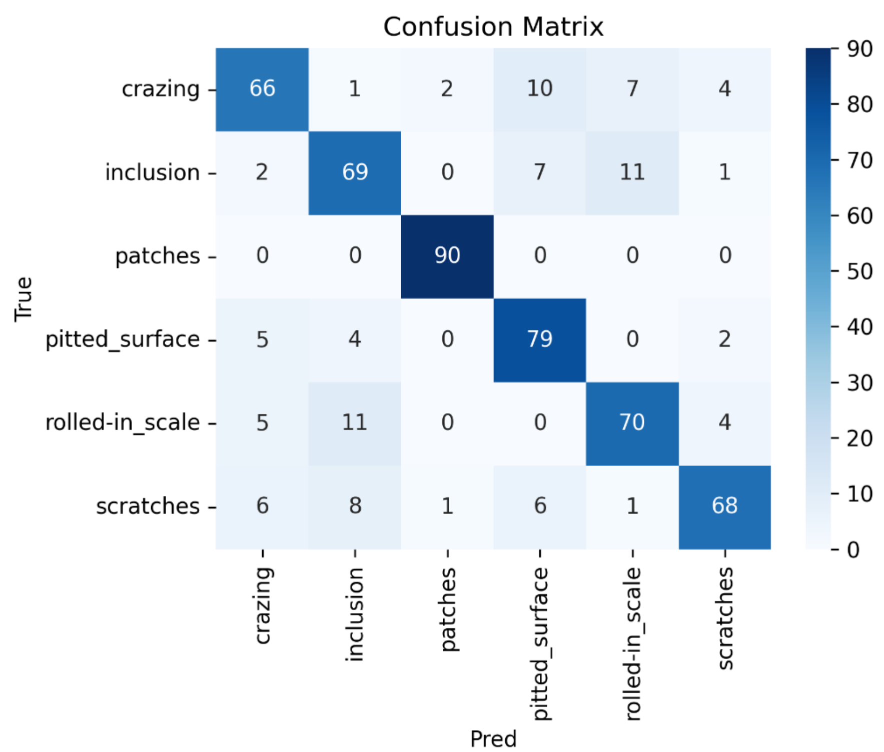
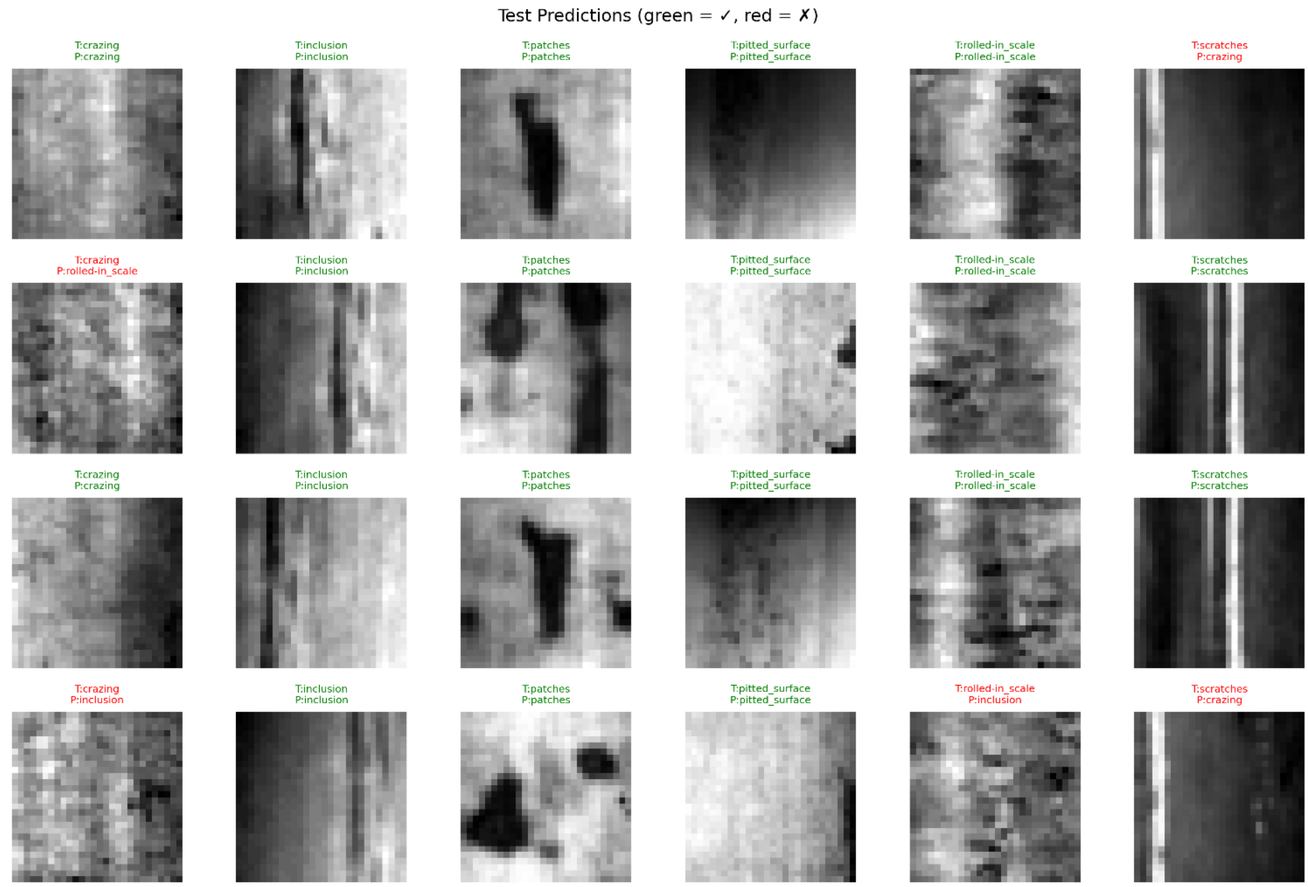
```
==========================================================================================
Layer (type:depth-idx)                                    Output Shape              Param #
==========================================================================================
ViT                                                       [64, 6]                   3,264
├─Unfold: 1-1                                             [64, 16, 49]              --
├─Linear: 1-2                                             [64, 49, 64]              1,088
├─Dropout: 1-3                                            [64, 50, 64]              --
├─Transformer: 1-4                                        [64, 50, 64]              --
│    └─ModuleList: 2-1                                    --                        --
│    │    └─ModuleList: 3-1                               --                        82,432
│    │    └─ModuleList: 3-2                               --                        82,432
│    │    └─ModuleList: 3-3                               --                        82,432
│    │    └─ModuleList: 3-4                               --                        82,432
│    │    └─ModuleList: 3-5                               --                        82,432
│    │    └─ModuleList: 3-6                               --                        82,432
├─LayerNorm: 1-5                                          [64, 64]                  128
├─Sequential: 1-6                                         [64, 6]                   --
│    └─Linear: 2-2                                        [64, 128]                 8,320
│    └─GELU: 2-3                                          [64, 128]                 --
│    └─Dropout: 2-4                                       [64, 128]                 --
│    └─Linear: 2-5                                        [64, 6]                   774
==========================================================================================
Total params: 508,166
Trainable params: 508,166
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 32.31
==========================================================================================
Input size (MB): 0.20
Forward/backward pass size (MB): 178.65
Params size (MB): 2.02
Estimated Total Size (MB): 180.87
==========================================================================================
```




Confusion Matrix
True
Pred
crazing
inclusion
patches
pitted_surface
rolled-in_scale
scratches
66 1 2 10 7 4
2 69 0 7 11 1
0 0 90 0 0 0
5 4 0 79 0 2
5 11 0 0 70 4
6 8 1 6 1 68
90
80
70
60
50
40
30
20
10
0


Test Predictions (green = ✓, red = ✗)
T:crazing P:crazing
T:inclusion P:inclusion
T:patches P:patches
T:pitted_surface P:pitted_surface
T:rolled-in_scale P:rolled-in_scale
T:scratches P:crazing
T:crazing P:rolled-in_scale
T:inclusion P:inclusion
T:patches P:patches
T:pitted_surface P:pitted_surface
T:rolled-in_scale P:rolled-in_scale
T:scratches P:scratches
T:crazing P:crazing
T:inclusion P:inclusion
T:patches P:patches
T:pitted_surface P:pitted_surface
T:rolled-in_scale P:rolled-in_scale
T:scratches P:scratches
T:crazing P:inclusion
T:inclusion P:inclusion
T:patches P:patches
T:pitted_surface P:pitted_surface
T:rolled-in_scale P:inclusion
T:scratches P:crazing

6. Briefly explain the role of patch embedding and positional encoding in ViT. You may include parts of your Step 3 model code to support your explanation

So, patch embedding is kinda like slicing a big pizza into smaller slices. In our code, we chop each 28×28 image into 4×4 squares (that's 49 little patches), flatten each one into a list of numbers, and then run it through a linear layer to get a 64-element "token." That way, the Transformer can handle images just like it handles words in a sentence.

Positional encoding is like giving each slice its own "address" so the model knows which slice came from the top-left or bottom-right. Without that, the model wouldn't know the order — it'd be like reading words out of order and trying to understand a story. We just add a learned vector to each patch token so the model learns spatial location.

7. Describe which hyperparameters you tuned, why you chose them, and how they affected your final accuracy.

- **learning rate (LR):** I used 3×10^{-4} because it made training smooth. If I cranked it up, the model freaked out and accuracy bounced all over.
- **batch size:** I chose 64 since Colab GPU could handle it without slowing too much. Smaller batches were jittery, bigger batches got slow.
- **patch size:** 4 worked well — 7×7 patches gave enough detail without choking my computer.
- **dim (token size):** 64 felt just right. Smaller (like 32) learned slow; bigger (128) was a bit better but took forever.
- **depth & heads:** I used 6 layers and 4 heads. That combo reached around 84% accuracy. More layers or heads only helped a tiny bit but really slowed training.
- **epochs:** I trained for 30 epochs. By then I hit about 84%. I found that set 25 epochs can not reach to the highest ACC and If I went to 50, it just wiggled up and down (overfitting).

8. Compare ViT and CNN for image classification: what are the main differences, and when might one be preferred over the other using the provided dataset?

- **CNNs** use little filters that look at one small neighborhood at a time, and they're super good when you don't have tons of data. They're fast and have built-in "image bias."
- **ViTs** use self-attention so every patch can talk to every other patch right away. **That's awesome for catching global patterns** (like overall texture across the whole photo). But they need more data (or good regularization) to not overfit.

On our defect images (about 1,800 total), ViT did great and hit ~84%. If I had only a couple hundred images, I might start with a CNN instead.

9. Report the final achieved test accuracy; explain whether you reached the >60% baseline — if not, describe what you tried and why it might have failed; if you did, explain how you achieved it.

I got around **84%** at the best epoch (and about 82–83% at epoch 30). That's way over the 60% requirement. I hit it by:

1. Choosing a sensible patch size (4×4).
2. Using a token dim of 64, depth 6, heads 4.
3. Adam optimizer with LR=3e-4.
4. Training for around 10–20 epochs to catch the peak before it wiggled too much.

If I hadn't reached 60%, I'd try early stopping, add a learning-rate scheduler, or throw in more data augmentation.

10. Based on the paper you referred to (Dosovitskiy et al., An Image is Worth 16x16 Words), please brief explain: You may include parts of your Step 3 model code to support your explanation.

a. How does the Vision Transformer process input images from start to finish?

- Input: 28×28 grayscale image.
- Cut into 4×4 patches → flatten → linear layer → get 49 tokens.
- Stick on a special [CLS] token at the front.
- Add positional embeddings so the model knows slice order.
- Run through 6 layers of Transformer (self-attention + feed-forward).
- Take the [CLS] token's output, feed it through a small MLP → get class scores.

b. How are the image patches divided and transformed into input sequences?

- 28×28 ÷ 4×4 → 7×7 = 49 patches.
- Each patch has size 4×4 = 16 pixels, we project those 16 numbers into a 64-dim vector.

c. How does the multi-head self-attention mechanism operate within the Transformer encoder?

- 28×28 ÷ 4×4 → 7×7 = 49 patches.
- Each patch has size 4×4 = 16 pixels, we project those 16 numbers into a 64-dim vector.

d. How does the model use the [CLS] token (or final output) to produce the final image classification?

- The [CLS] token's hidden state after the last layer is like a summary of the whole image.
- We normalize it (LayerNorm) and run it through an MLP head to predict which defect class it is.