YOGA POSES CLASSIFICATION

Classify yoga poses using a pre-trained Transformer with Graph Neural Network layers to jointly process images and pose graphs using a <CLS> token for accurate prediction

Dionigi Rodriguez, Valentina Zingarello

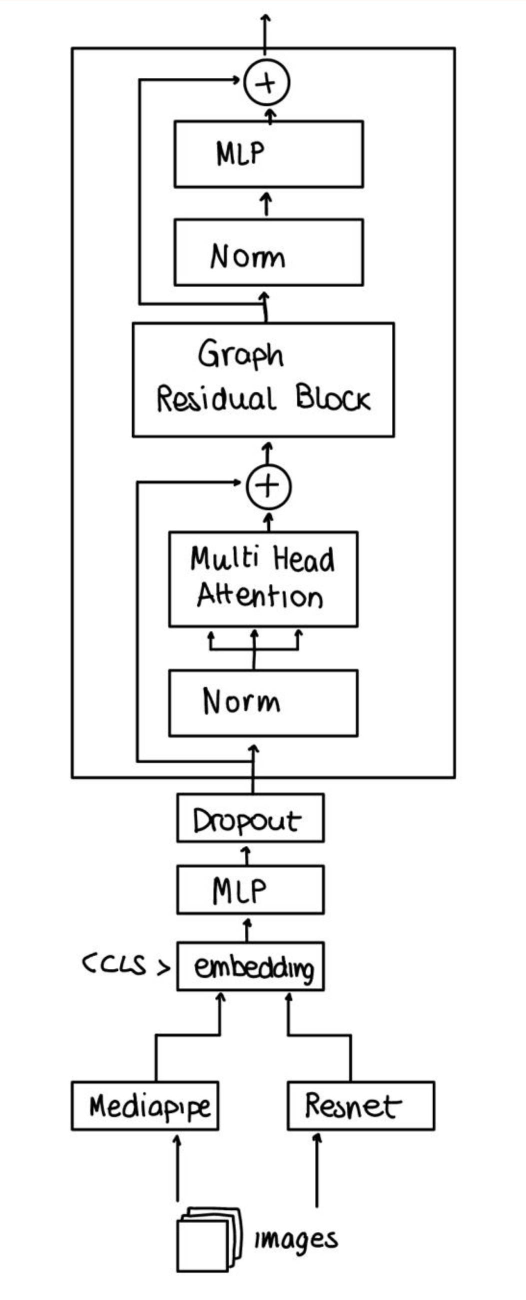
MEDIAPIPE

RESNET

GRAPH
RESIDUAL
BLOCK

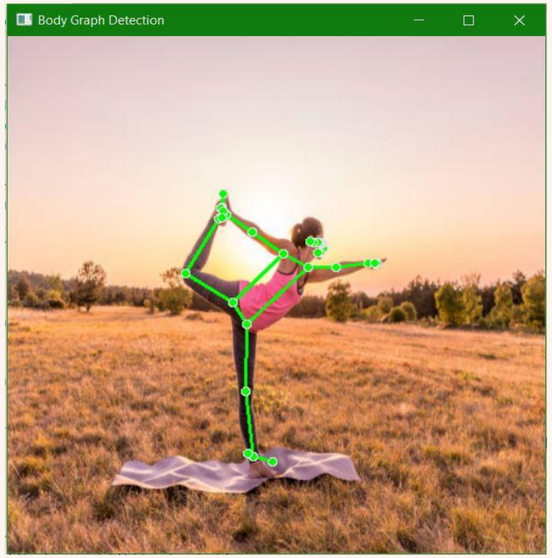
BERT

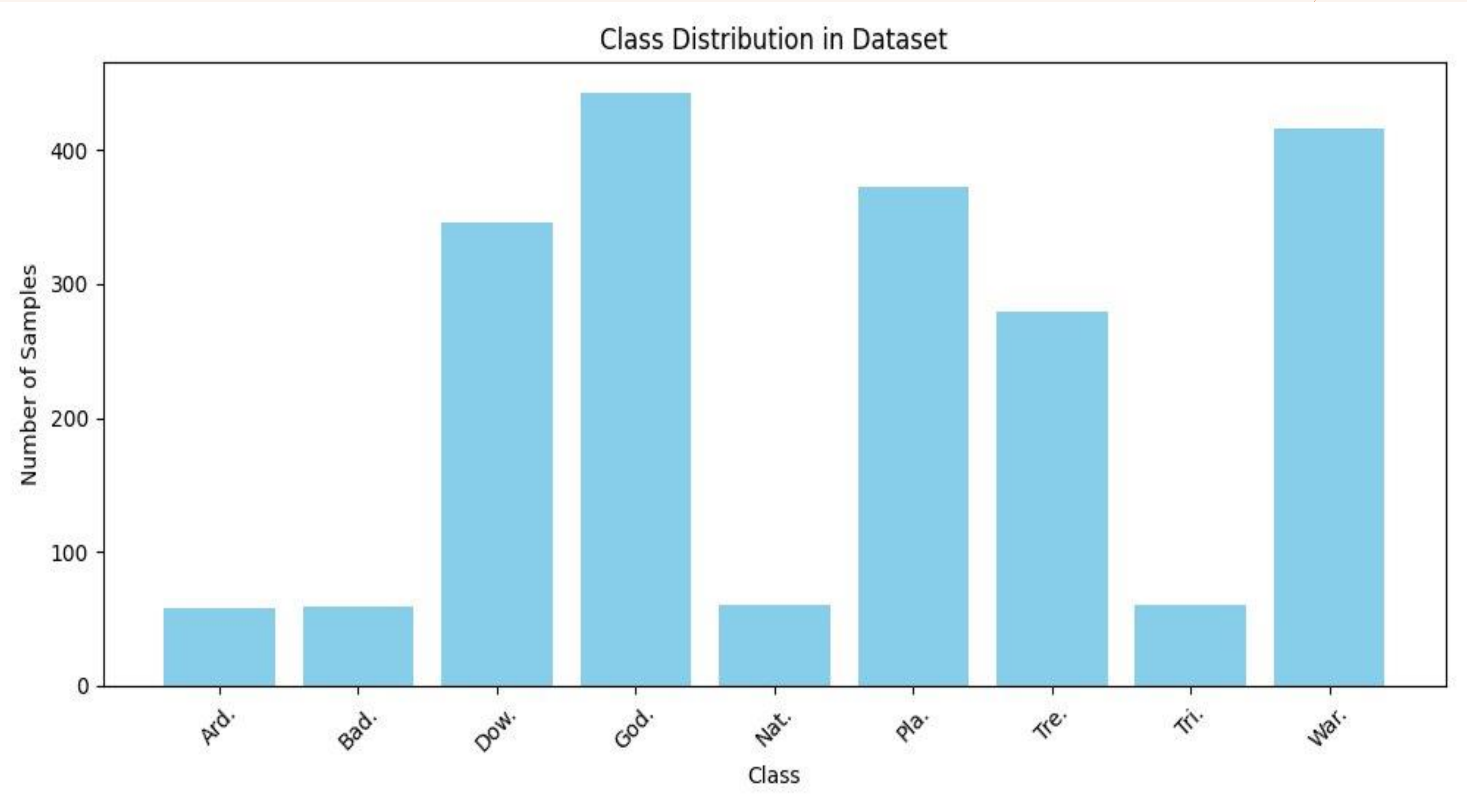
ARCHITECTURE COMPONENTS



DATASET

- Loaded image data from class-labeled directories.
- Normalized images to RGB and resizes them.
- Extracted pose landmarks using MediaPipe.
- Saved processed images and keypoints to disk.
- Converted images and landmarks to PyTorch tensors.
- Applied one-hot encoding to class labels.
- Shuffled and splits data into training and test sets.
- Created separate datasets for images, keypoints, and edges.
- Returned batched data loaders for model training.




Class Distribution in Dataset
Number of Samples
400
300
200
100
0
Ard.
Bad.
Dow.
God.
Nat.
Pla.
Tre.
Tri.
War.
Class

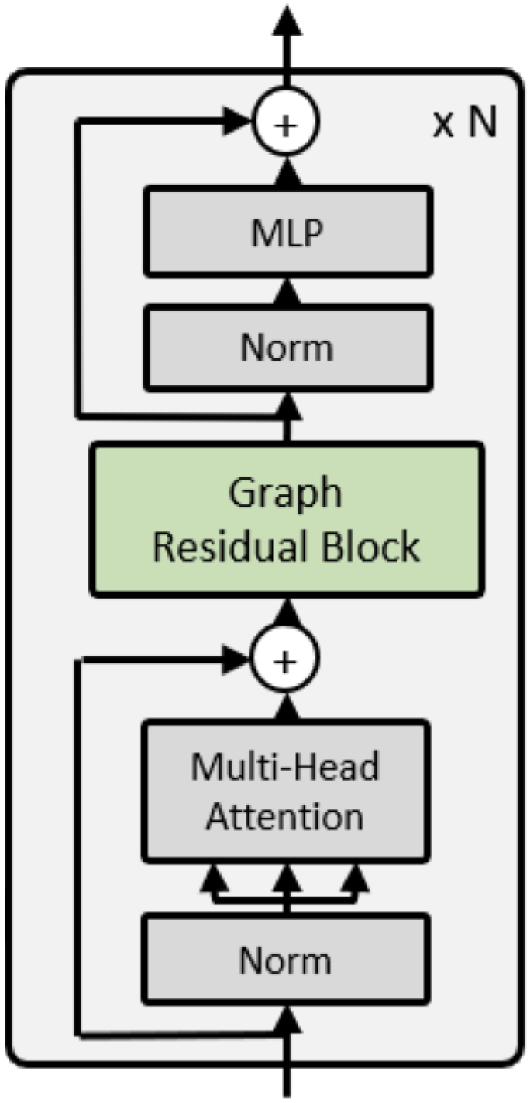
EMBEDDINGS

- Combines three sources of information for each sample:
- **CNN visual features** from ResNet
- **3D landmark coordinates** (x, y, z, visibility)
- **Skeleton graph structure** as a flattened adjacency matrix
- All components are **concatenated** into a single feature vector
- A **[CLS] token** is prepended to the sequence for transformer-based processing
- Final tensor is **replicated** to form a sequence input compatible with BERT+GNN layers

```
 #print(buildAdjMat(ed).device)
 emb= torch.concat((elem,concatCoor(vt),adjMat))
 emb = torch.stack([emb for x in range(mI+1)])
 emb = torch.concat((clsToken,emb))
#print("shape")
```

BERT

- Uses a pre-trained BERT-base model as the core transformer encoder
- Replaces standard BERT encoder layers with custom `BertGraphEncoder` modules
- Each `BertGraphEncoder` injects graph structure via a GraphResidualBlock into attention output
- BERT attention captures global context, GCN layers capture local graph relations

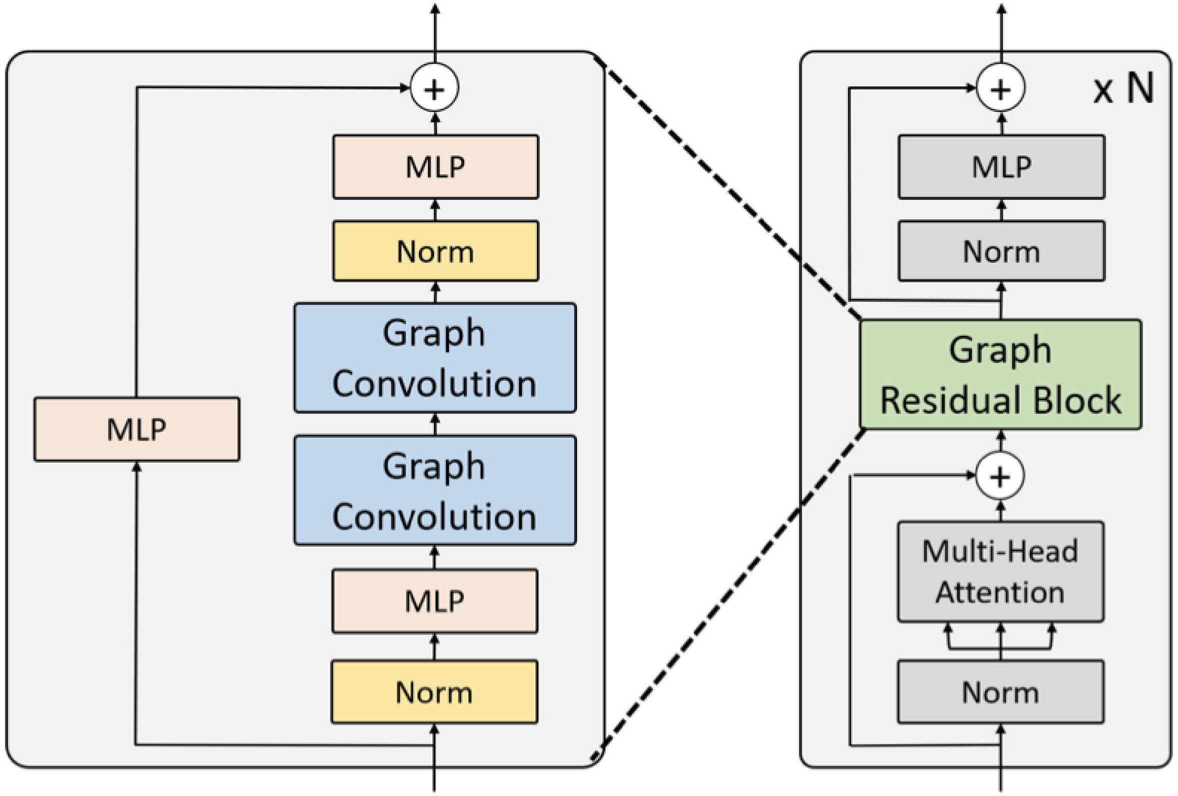


GRAPH RESIDUAL BLOCK

- Starts with LayerNorm and MLP for feature transformation
- Applies two GCNConv layers with GELU activations for message passing
- Includes a residual connection with its own MLP to preserve input information

```
class GraphResidualBlock(nn.Module):
    def __init__(self, in_channels, out_channels, hiddenDim):
        super().__init__()

        self.norm1 = nn.LayerNorm(hiddenDim)
        # mlp1 layer
        self.mlp1 = nn.Sequential(
            nn.Linear(hiddenDim,hiddenDim),
            nn.GELU())
        # graph conv
        self.conv1 = GCNConv(in_channels, out_channels)
        #gelu
        self.gelu1 = nn.GELU()
        # graph conv
        self.conv2 = GCNConv(in_channels, out_channels)
        #gelu
        self.gelu2 = nn.GELU()
        # norm
        self.norm2 = nn.LayerNorm(hiddenDim)
        # mlp2
        self.mlp2 = nn.Sequential(
            nn.Linear(hiddenDim,hiddenDim),
            nn.GELU())
        # + residualmlp
        self.mlp3 = nn.Sequential(
            nn.Linear(hiddenDim,hiddenDim),
            nn.GELU())
```



TRAINING PIPELINE

Input: `(Image, Graph)` pairs per sample

Loss: `CrossEntropyLoss` with class weighting to handle imbalance

Early Stopping: Stops if validation loss doesn't improve for 3 epochs

Best model checkpointing based on validation loss.

GRID SEARCH

```
param_grid = {
    'lr': [1e-4,1e-5],
    'weight_decay': [1e-4,1e-5],
    'dropout_rate': [0.2,0.3, 0.5],
    'numLayers': [2, 4, 6]
}
```

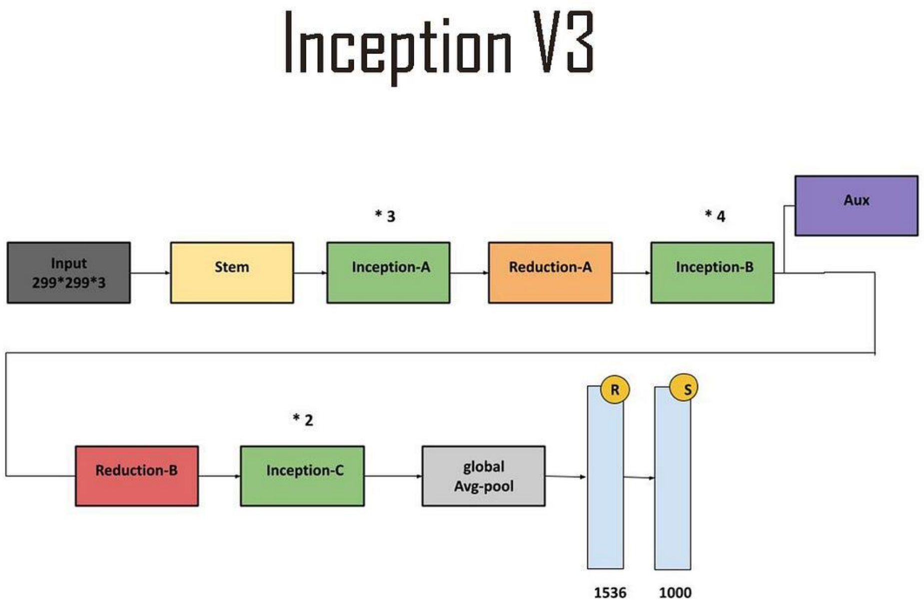
5 classes classification

```
Best parameters:
{'lr': 1e-05, 'weight_decay': 1e-05, 'dropout_rate': 0.5, 'numLayers': 2}
Best validation accuracy: 95.1814
```

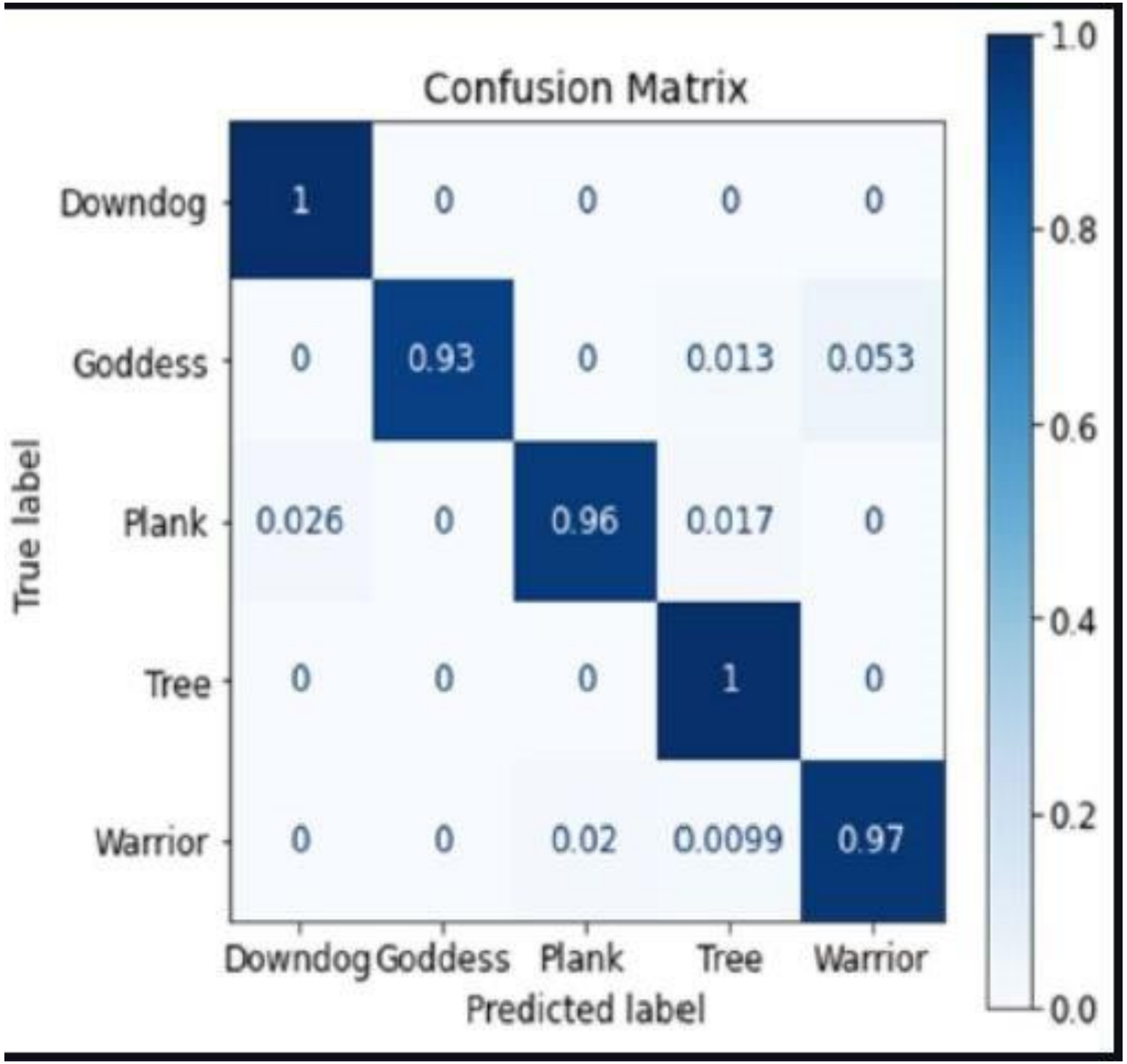
9 classes classification

```
Best parameters:
{'lr': 1e-05, 'weight_decay': 1e-05, 'dropout_rate': 0.5, 'numLayers': 6}
Best validation accuracy: 0.9605
```

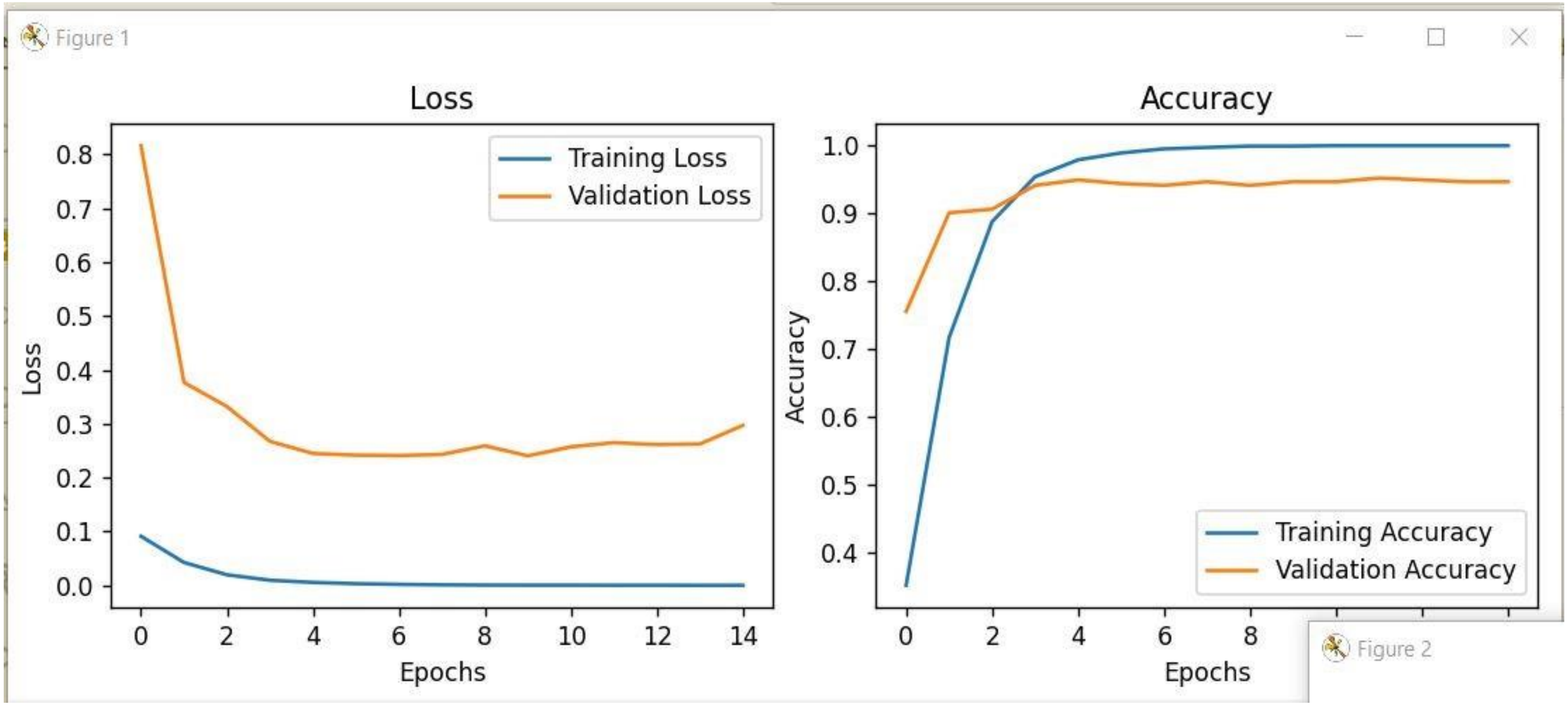
YOGACONV2D & INCEPTIONV3



Model	Accuracy (Validation)	Accuracy (Test)	Precision	Recall	F1 Score
YogaConvo2d (MediaPipe)	99.62%	97.09%	0.97	0.97	0.97
YogaConvo2d (Non-MediaPipe)	89.97%	89.36%	0.89	0.88	0.89
InceptionV3 (MediaPipe)	95.09%	94.39%	0.95	0.94	0.94


Confusion Matrix
Downdog
Goddess
Plank
Tree
Warrior
True label
1
0
0
0
0
0
0.93
0
0.013
0.053
0.026
0
0.96
0.017
0
0
0
0
1
0
0
0
0.02
0.0099
0.97
Downdog
Goddess
Plank
Tree
Warrior
Predicted label
1.0
0.8
0.6
0.4
0.2
0.0

BERT + GRAPH RESIDUAL BLOCK 5



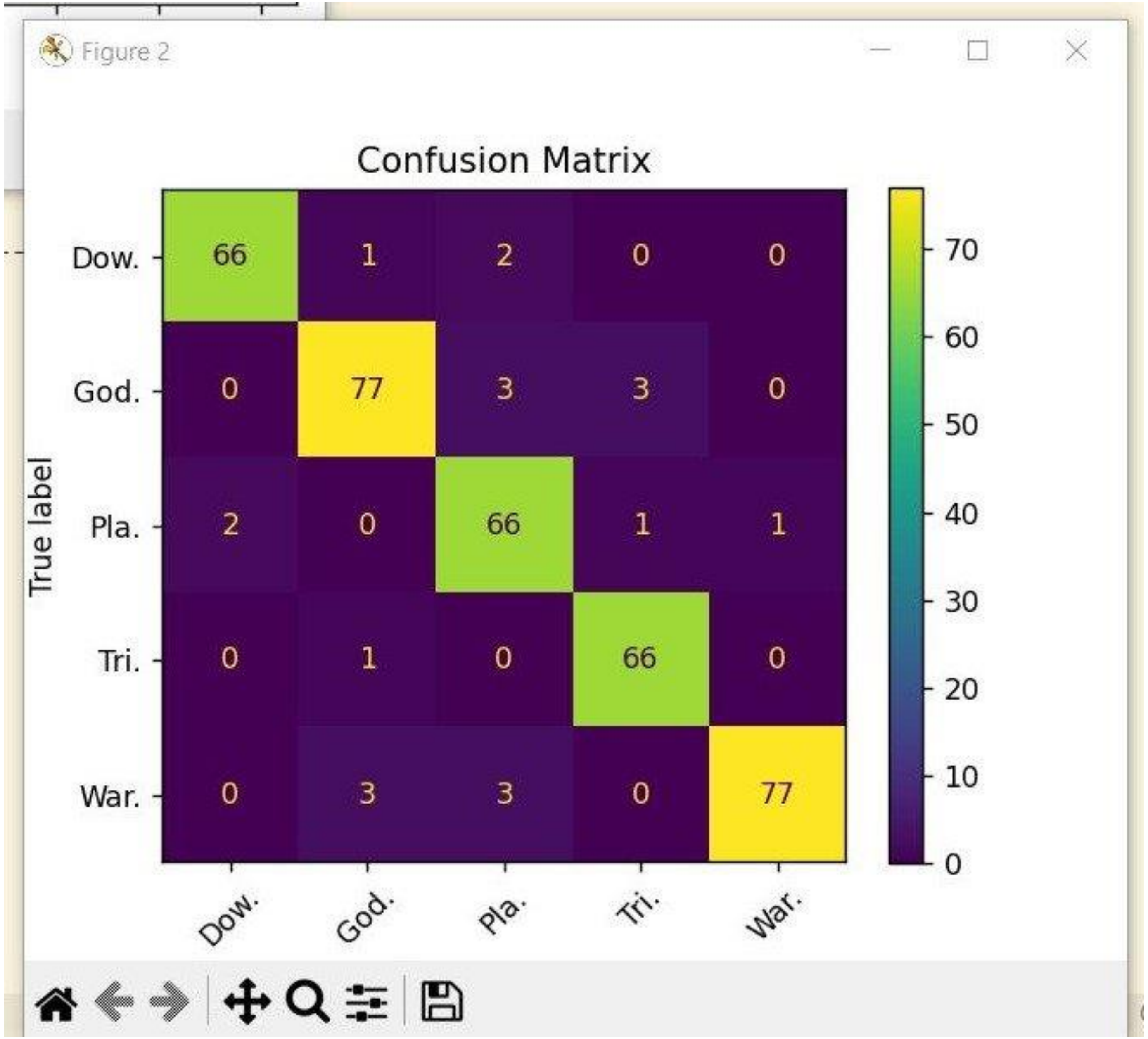


Figure 2
Confusion Matrix
True label
Dow.
God.
Pla.
Tri.
War.
66 1 2 0 0
0 77 3 3 0
2 0 66 1 1
0 1 0 66 0
0 3 3 0 77
70
60
50
40
30
20
10
0
Dow.
God.
Pla.
Tri.
War.

94.6236559139785

---

	precision	recall	f1-score	support
Dow.	0.9706	0.9565	0.9635	69
God.	0.9390	0.9277	0.9333	83
Pla.	0.8919	0.9429	0.9167	70
Tri.	0.9429	0.9851	0.9635	67
War.	0.9872	0.9277	0.9565	83
accuracy			0.9462	372
macro avg	0.9463	0.9480	0.9467	372
weighted avg	0.9474	0.9462	0.9464	372

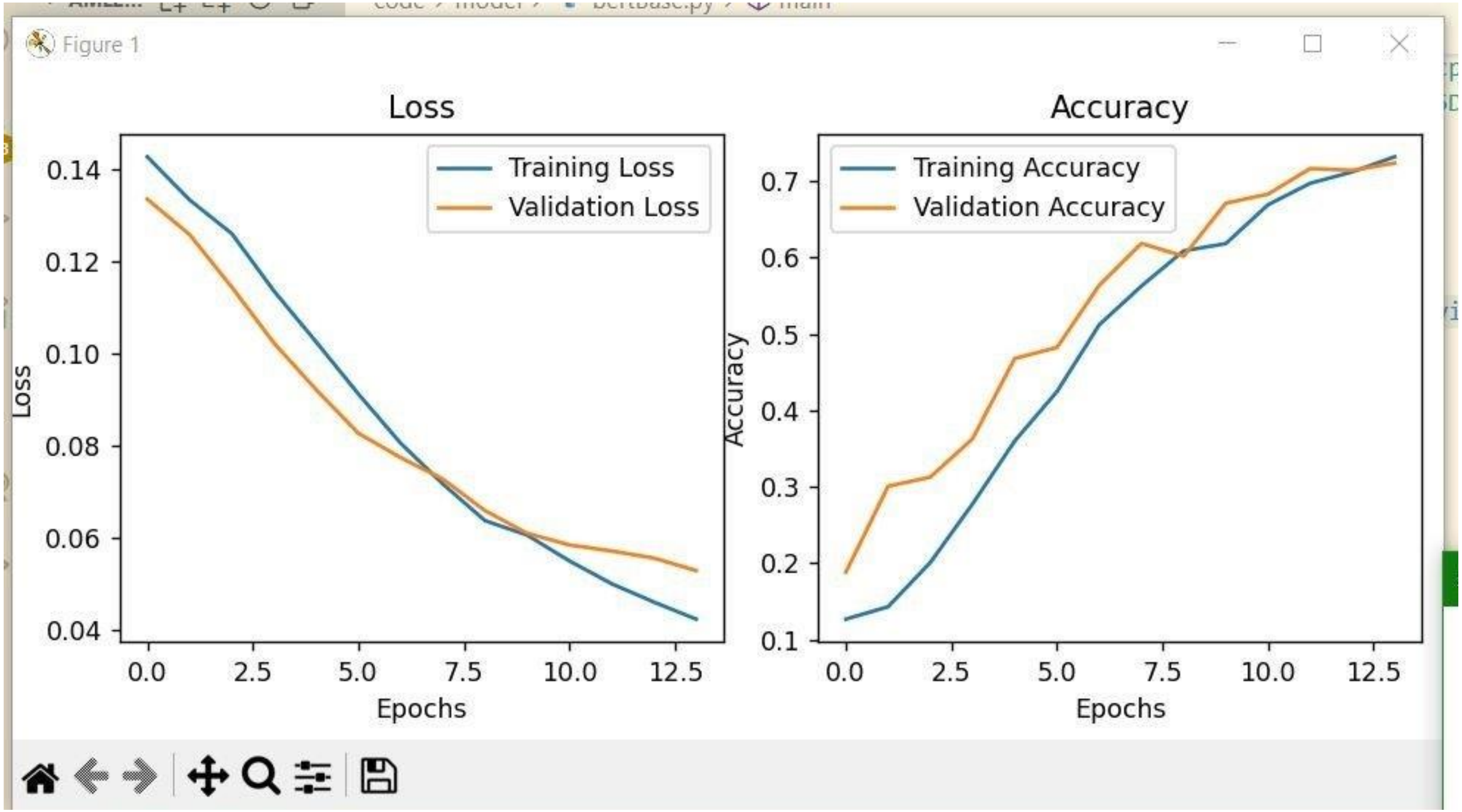


Figure 1
Loss
Training Loss
Validation Loss
Loss
0.14
0.12
0.10
0.08
0.06
0.04
0.0
2.5
5.0
7.5
10.0
12.5
Epochs
Accuracy
Training Accuracy
Validation Accuracy
Accuracy
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
2.5
5.0
7.5
10.0
12.5
Epochs

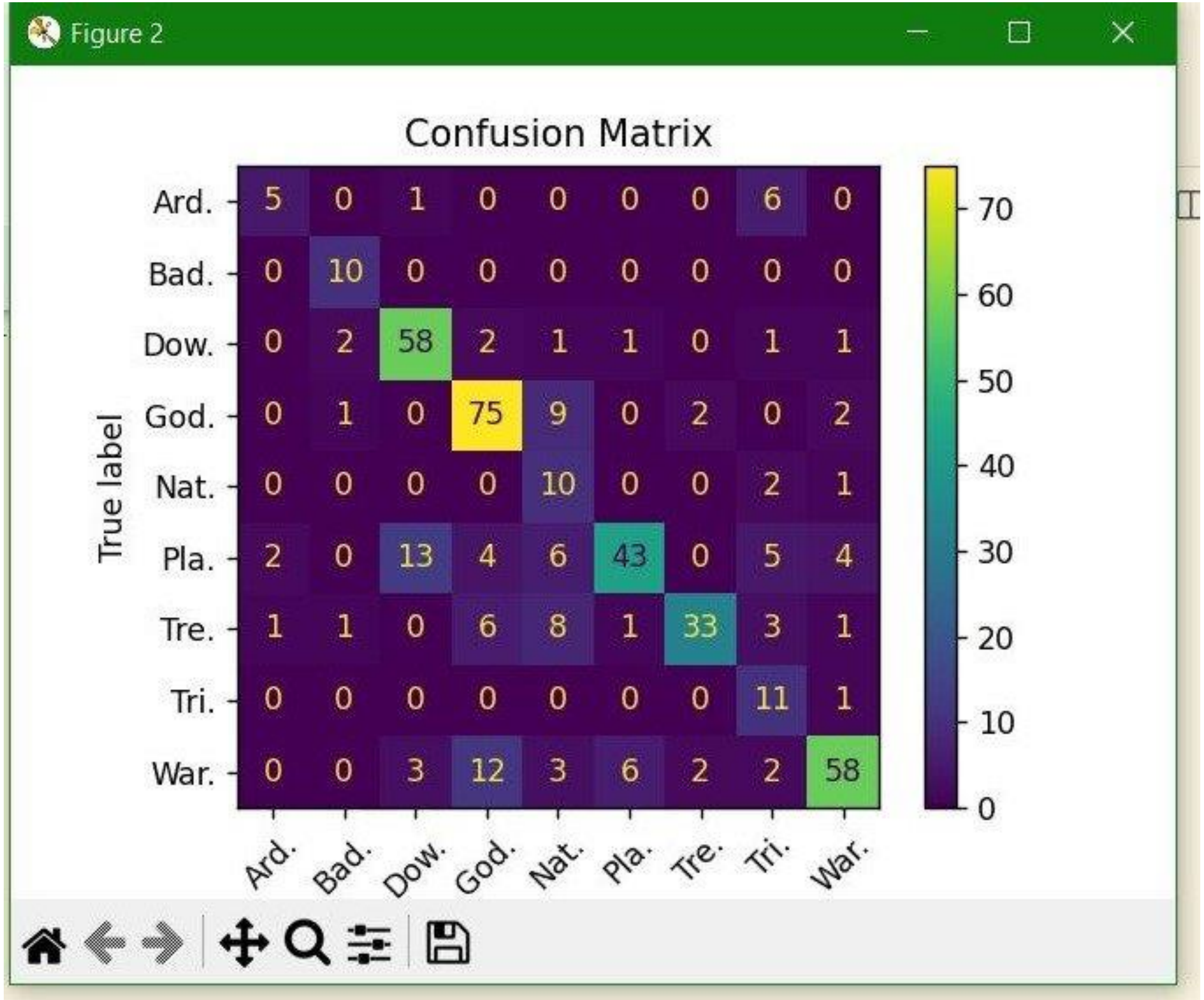
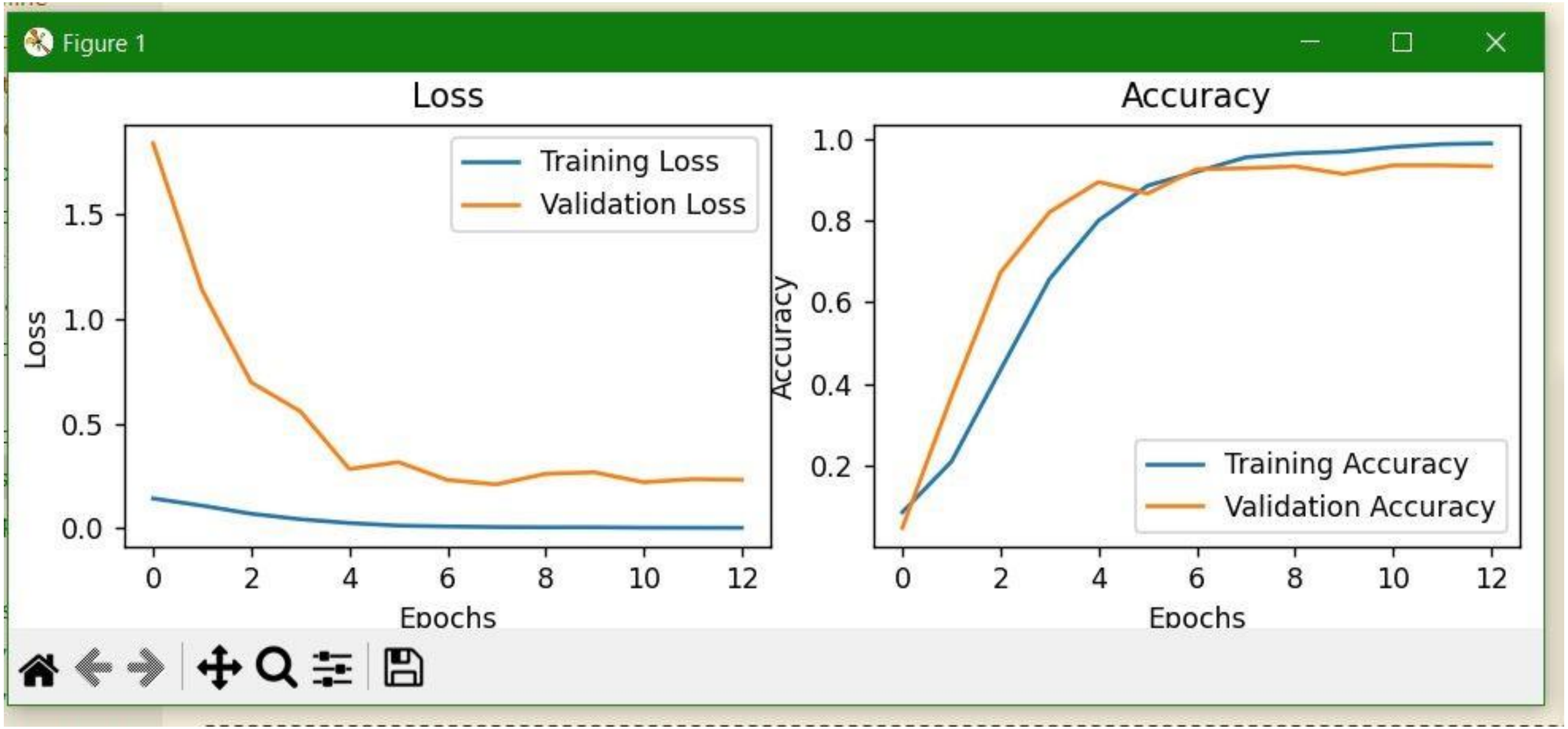


Figure 2
Confusion Matrix
True label
Ard.
Bad.
Dow.
God.
Nat.
Pla.
Tre.
Tri.
War.
5 0 1 0 0 0 0 6 0
0 10 0 0 0 0 0 0 0
0 2 58 2 1 1 0 1 1
0 1 0 75 9 0 2 0 2
0 0 0 0 10 0 0 2 1
2 0 13 4 6 43 0 5 4
1 1 0 6 8 1 33 3 1
0 0 0 0 0 0 0 11 1
0 0 3 12 3 6 2 2 58
70
60
50
40
30
20
10
0

	precision	recall	f1-score	support
Ard.	0.6250	0.4167	0.5000	12
Bad.	0.7143	1.0000	0.8333	10
Dow.	0.7733	0.8788	0.8227	66
God.	0.7576	0.8427	0.7979	89
Nat.	0.2703	0.7692	0.4000	13
Pla.	0.8431	0.5584	0.6719	77
Tre.	0.8919	0.6111	0.7253	54
Tri.	0.3667	0.9167	0.5238	12
War.	0.8529	0.6744	0.7532	86
accuracy			0.7232	419
macro avg	0.6772	0.7409	0.6698	419
weighted avg	0.7815	0.7232	0.7322	419

BERT + GRAPH RESIDUAL BLOCK 9



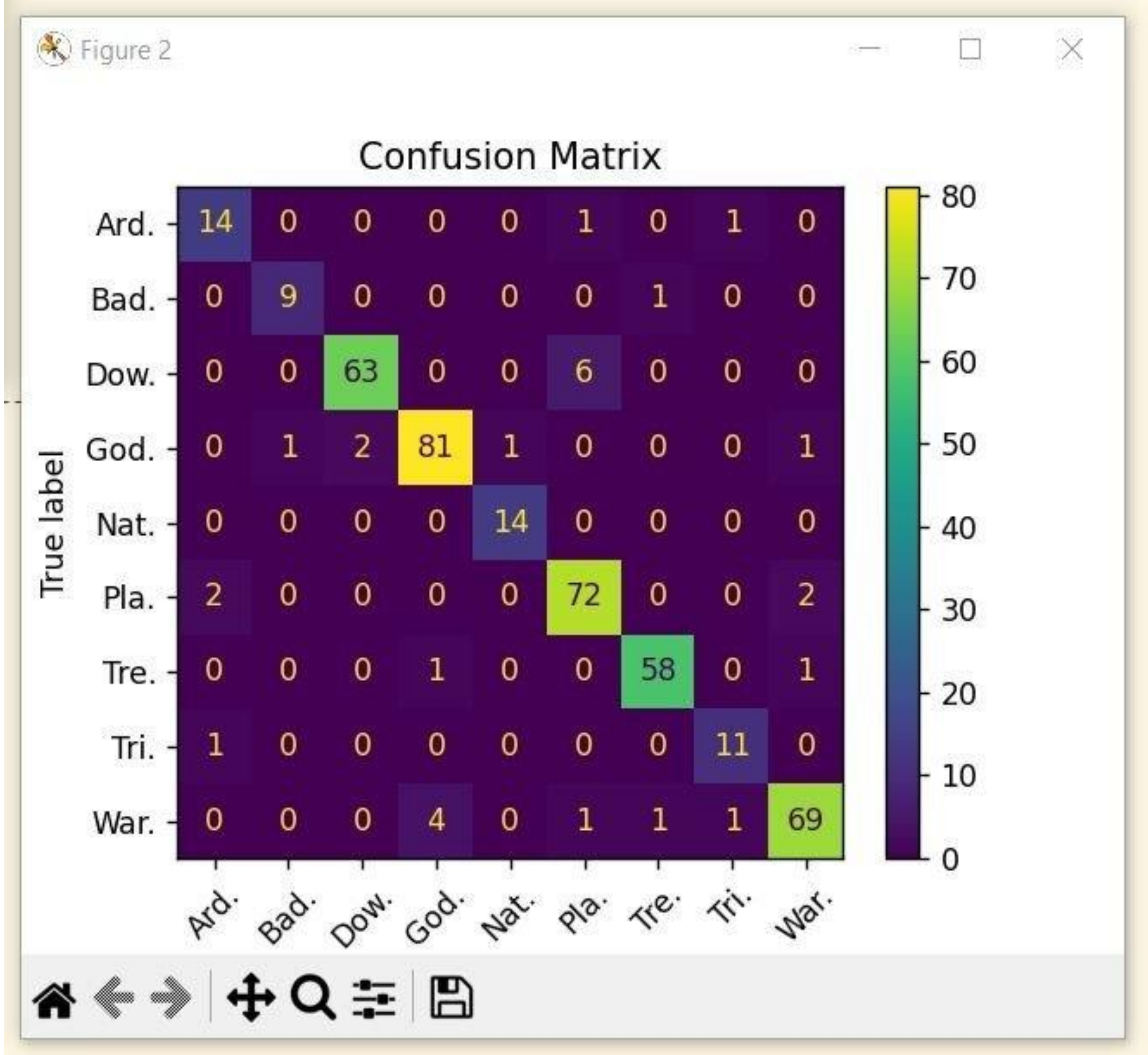


Figure 2
Confusion Matrix
True label
Ard.
Bad.
Dow.
God.
Nat.
Pla.
Tre.
Tri.
War.
14 0 0 0 0 1 0 1 0
0 9 0 0 0 0 1 0 0
0 0 63 0 0 6 0 0 0
0 1 2 81 1 0 0 0 1
0 0 0 0 14 0 0 0 0
2 0 0 0 0 72 0 0 2
0 0 0 1 0 0 58 0 1
1 0 0 0 0 0 0 11 0
0 0 0 4 0 1 1 1 69
0
10
20
30
40
50
60
70
80

	precision	recall	f1-score	support
Ard.	0.8235	0.8750	0.8485	16
Bad.	0.9000	0.9000	0.9000	10
Dow.	0.9692	0.9130	0.9403	69
God.	0.9419	0.9419	0.9419	86
Nat.	0.9333	1.0000	0.9655	14
Pla.	0.9000	0.9474	0.9231	76
Tre.	0.9667	0.9667	0.9667	60
Tri.	0.8462	0.9167	0.8800	12
War.	0.9452	0.9079	0.9262	76
accuracy			0.9332	419
macro avg	0.9140	0.9298	0.9213	419
weighted avg	0.9344	0.9332	0.9334	419

Q&A

SOURCES

- Mesh Graphormer: https://arxiv.org/pdf/2104.00272
- Convolutional Mesh Regression for Single-Image Human Shape Reconstruction: https://arxiv.org/pdf/1905.03244
- **Yoga-Pose-Classification-and-Skeletonization**