

Deepfake Classification: Project Report

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1 Machine Learning Models

The models tested for classification were Support Vector Machine (SVM) and Neural Networks.

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2 Support Vector Machine (SVM)

- **Description:** Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection [2].
- **Hyperparameters:** Regularization parameter C , kernel type.
- **Implementation:** Used `sklearn.svm.SVC`.

2.1 SVM Preprocessing

2.1.1 Feature Extraction

Image features were represented using color histograms for the RGB color space with 256 bins per channel.

Example code for feature extraction:

```
def get_image_features_from_images(  
    images: np.ndarray,  
) -> np.ndarray:  
    BINS = 256  
    image_features = []  
    for image in images:  
        histogram_red = np.histogram(image[:, :, 0],  
                                     bins=BINS, range=(0, 256))[0]  
        histogram_green = np.histogram(image[:, :, 1],  
                                       bins=BINS, range=(0, 256))[0]  
        histogram_blue = np.histogram(image[:, :, 2],  
                                      bins=BINS, range=(0, 256))[0]  
        histogram = np.concatenate(  
            [histogram_red, histogram_green, histogram_blue]  
        )  
        image_features.append(histogram)  
    return np.array(image_features)
```

Example for how a feature vector looks like (the size of the vector is $256 \times 3 = 768$):

```
[ 7  4  3  7  4  4  5  5  3  8  6  6 12  4  7 14  7 10  
 8 10 12  9  6 10  8  8 10  5  5 13 14  7 16  9  7 10  
14  8 16 10  9  7 14  7  9 13 10 10 13  9  8  6  6  7  
 6  9  5  3  3  7 11  6  9  4  7  6  9  4  7  7 11  7  
 9  8 10  5  8  5  9  7  8  3 12  8  9 11 11 14 12 10  
11  7 15 16 11 13 10 14 14 22 17 15 23 20 22 30 23 14  
27 23 22 18 28 22 21 30 19 28 20 23 19 15 20 27 27 20  
18 22 20 19 29 29 25 21 23 20 24 23 34 34 43 30 55 72  
98 92 99 102 129 145 154 150 157 160 180 207 222 211 227 247 296 264  
258 340 322 346 310 410 373 241 274 258 152  63  26  27  33  18  19  11  
15  7  6  8 15 10  9 10 11  1 10  4  8  7  5  2  7  6  
 5  8  4  2  5  3  3  6  9  9 20 18 18 26 26 39 33 53  
66 72 70 102 132 131 105 76 73 52 30 23 14 11  2  2  1  2  
 1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  
 0  0  0  0 67 37 33 23 23 23 16 21 21 19 17 13 13 14  
10 11  6  9 15 10 11  9 12 11  7  8 10  7  8 10  4  5  
 5  5 12 10  6 10  7  8  9  4 11 12 10  6  5  7  8 10  
 7  6  8 14 11  4 10 16 10 13  7 12  7 15  8 12 13 13  
18 14 21 21 13 11  8 15 22 16 20 17 17 17 29 28 35 30  
28 31 33 28 16 19 29 26 25 24 20 39 30 31 33 52 49 57  
85 97 133 112 118 171 192 166 164 175 208 202 206 250 262 270 304 370  
353 398 411 339 316 318 345 291 235 129 76 41 32 27 18 23 14 19  
 7  9  9  9  6  5  1  2  4  5  4  5  3  1  4  8  5  7
```

3	5	3	4	1	0	6	6	3	2	8	8	5	8	11	13	18	21
22	16	31	27	27	45	55	47	59	80	112	104	117	98	82	56	40	32
23	19	14	16	10	3	4	2	2	1	0	0	0	0	0	0	0	0
0	0	1	1	0	0	1	0	2	0	0	0	0	0	1	0	1	1
1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	36	28	35	38	35	26	27	20	19	26
17	14	18	16	19	17	16	19	25	12	16	12	14	18	14	18	18	21
20	20	26	26	14	13	18	25	22	26	25	25	28	32	27	29	30	36
35	37	29	39	29	35	41	39	43	37	38	30	30	33	47	36	43	46
48	48	65	62	77	101	143	148	221	210	221	227	204	249	273	315	328	403
455	515	466	443	368	339	310	266	159	89	48	39	20	16	10	10	8	5
6	3	8	3	5	3	3	3	5	1	3	6	3	7	4	5	4	1
5	6	7	2	2	5	1	9	1	3	2	3	4	6	13	11	12	21
21	14	20	16	22	22	41	32	46	36	51	68	82	90	86	91	89	69
57	55	39	20	19	22	8	15	6	15	6	1	4	1	2	1	2	0
0	0	0	0	0	0	0	0	1	3	0	0	0	0	1	0	0	0
1	0	2	0	1	0	0	0	0	1	0	0	1	1	0	0	1	1
1	1	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0
1	0	1	0	1	2	0	1	0	0	1	1	2	1	0	0	1	0
0	0	0	1	0	1	0	0	0	0	0	0	0]					

Example color histogram (Figure 2) for Figure 1:

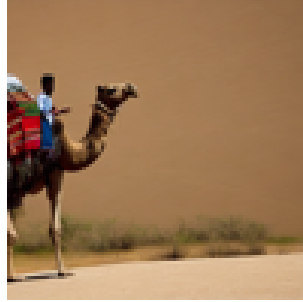


Figure 1: Example Image

2.1.2 Preprocessing Steps

- **Reshaping:** Images were reshaped from a 100*100*3 format to 3 vectors of size 10000, for each color channel (R, G, B).
- **Feature extraction:** Color histograms were computed into a single vector of size 768 (3* 256 bins per channel) for each image.
- **Normalization:** Pixel values were normalized using the l2 norm $\|x\|_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$.

2.2 SVM Hyperparameter Tuning

- **Parameter:** C (Regularization)
- **Values tested:** 0.01, 0.1, 1, 10, 100

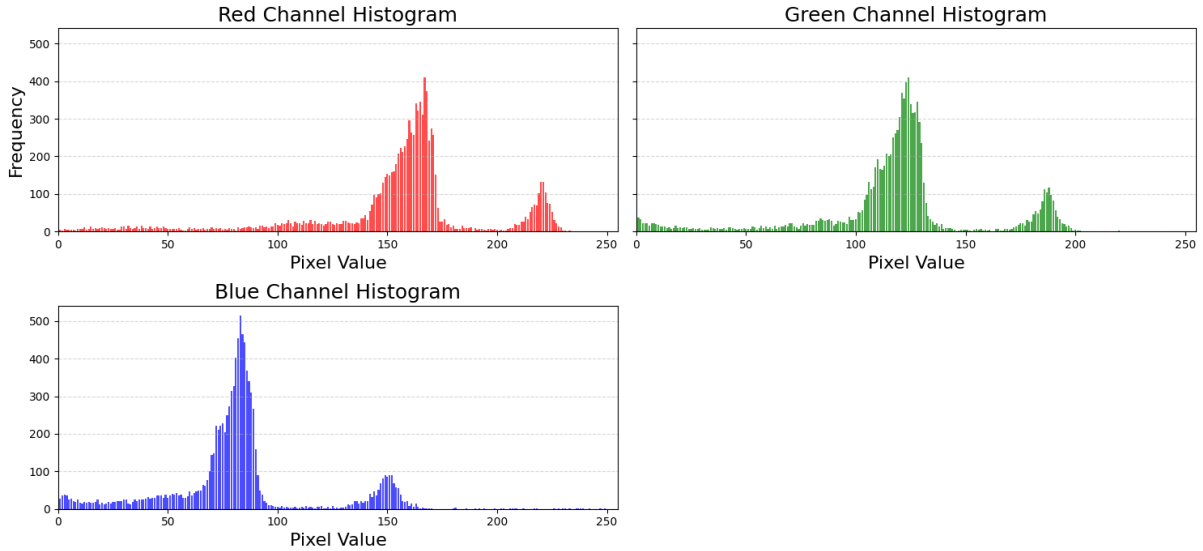


Figure 2: Example Color Histogram for an Image

Table 1: SVM Validation Accuracy for Different C Values

C	0.01	0.1	1	10	100
Accuracy	0.5352	0.624	0.7296	0.7136	0.7152

2.3 Confusion Matrix for SVM (Figure 4)

The best SVM model was selected with $C = 1$ based on validation accuracy.

2.4 Performance Comparison

Table 2: Validation Accuracy for Different Models

Model	Best Hyperparameters	Validation Accuracy
SVM	$C = 1$	0.7296
K-NN	$k = 5$	(insert value)

2.5 Convolutional Neural Network (CNN)

- **Description:** Convolutional Neural Network (CNN) is an advanced version of artificial neural networks (ANNs), primarily designed to extract features from grid-like matrix datasets. This is particularly useful for visual datasets such as images or videos, where data patterns play a crucial role. CNNs are widely used in computer vision applications due to their effectiveness in processing visual data [1].
- **Hyperparameters:** Learning rate, number of training epochs.
- **Implementation:** The main components are the `NeuralNetwork` class (defining the architecture and forward pass).

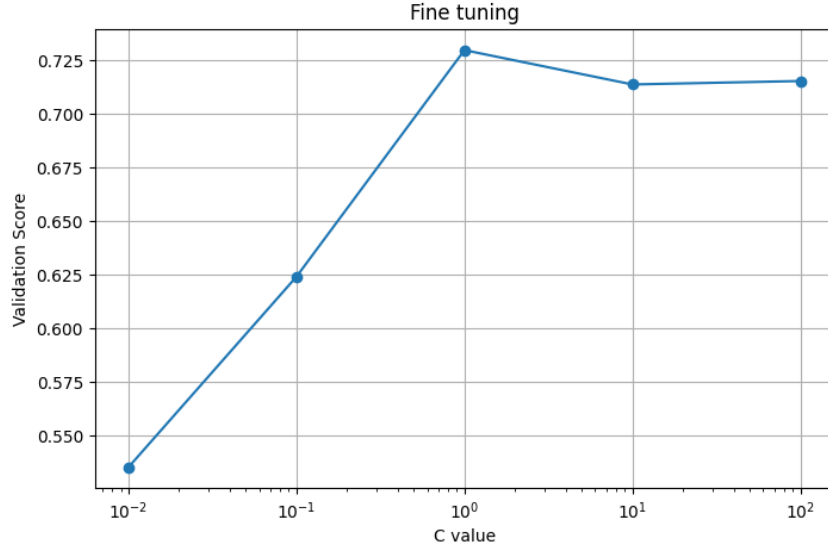


Figure 3: Validation Score vs. C for SVM

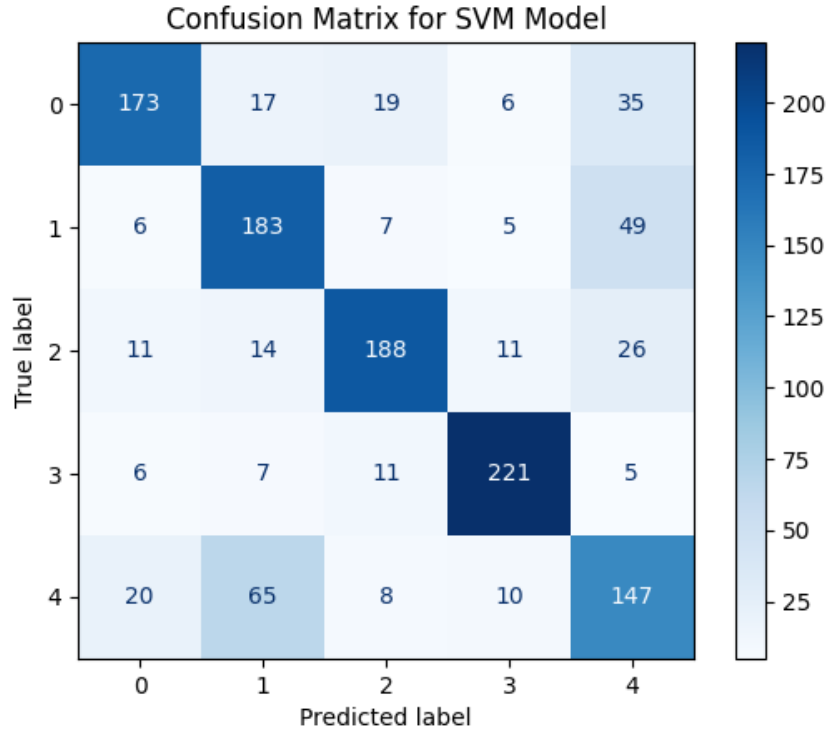


Figure 4: Confusion Matrix for SVM Model

2.6 CNN Preprocessing

Before being passed to the neural network, images undergo the following preprocessing steps:

- **Reshaping:** Each image is converted from the standard $100 \times 100 \times 3$ (height, width, RGB channels) format to $3 \times 100 \times 100$, as required by PyTorch's `Conv2d` layers. This format places the color channels first.

- **Normalization:** All pixel values are standardized using the dataset mean and standard deviation.
- **Batching:** Images and their corresponding labels are grouped into batches using a `DataLoader`, which enables efficient mini-batch training and shuffling of the dataset.

This preprocessing pipeline ensures that the input data is compatible with the PyTorch model defined in `neural_network.py` and supports effective training.

2.7 Neural Network Structure

```
def get_image_features_from_images(
    images: np.ndarray,
) -> np.ndarray:
class NeuralNetwork(nn.Module):
    def __init__(self):
        super().__init__()

        # Define the relu function
        self.relu_fn = nn.ReLU()

        # Define the flatten function
        self.flatten = nn.Flatten()

        # Define dropout function
        self.dropout_fn = nn.Dropout(0.5)

        # Image has shape: 3 x 100 x 100

        # Layer 1
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.bn1_conv = nn.BatchNorm2d(32)
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2) # Output: 32 x 50 x 50

        # Layer 2
        self.conv2 = nn.Conv2d(
            in_channels=32, out_channels=64, kernel_size=3, padding=1
        )
        self.bn2_conv = nn.BatchNorm2d(64)
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2) # Output: 64 x 25 x 25

        # Layer 3
        self.conv3 = nn.Conv2d(
            in_channels=64, out_channels=128, kernel_size=3, padding=1
        )
        self.bn3_conv = nn.BatchNorm2d(128)
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2) # Output: 128 x 12 x 12

        # Neural Network Layers (Fully Connected Layers)
        # The input is the output of the last convolutional layer
        self.fc1 = nn.Linear(128 * 12 * 12, 512)
```

```

self.bn1_fc = nn.BatchNorm1d(512)
self.dropout1 = nn.Dropout(0.5)

self.fc2 = nn.Linear(512, 256)
self.bn2_fc = nn.BatchNorm1d(256)
self.dropout2 = nn.Dropout(0.5)

self.output_layer = nn.Linear(256, 5) # Assuming 5 output classes

def forward(self, x):
    # Convolutional layers
    x = self.pool1(self.relu_fn(self.bn1_conv(self.conv1(x))))
    x = self.pool2(self.relu_fn(self.bn2_conv(self.conv2(x))))
    x = self.pool3(self.relu_fn(self.bn3_conv(self.conv3(x))))

    # Flatten
    x = self.flatten(x)

    # Fully connected layers
    x = self.dropout_fn(self.relu_fn(self.bn1_fc(self.fc1(x))))
    x = self.dropout_fn(self.relu_fn(self.bn2_fc(self.fc2(x))))
    x = self.output_layer(x)
    return x

```

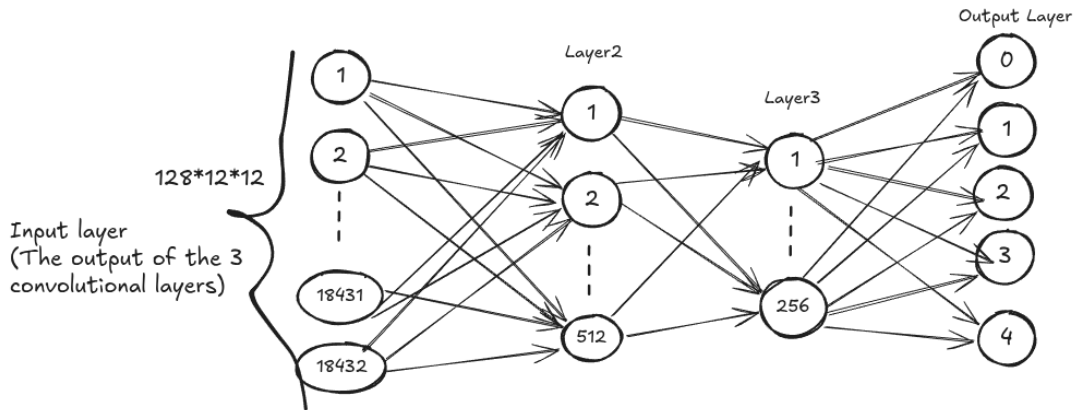


Figure 5: Neural Network Structure

2.7.1 CNN hyperparameter tuning

Parameter Tuned: Learning rate (see Table 3 and Figure 6)

The peak validation accuracy was achieved at a learning rate of 0.0001. After this point, the accuracy slightly decreased, indicating that lowering the learning rate further may have led to a steady decrease in accuracy.

Parameter Tuned: Epochs (see Table 4, and Figure 7)

The loss is in a steady decline, indicating that the model is learning effectively. The model was stopped at 10 epochs to prevent overfitting.

Table 3: CNN Validation Accuracy for Different Learning Rates

Learning Rate	Validation Accuracy (%)
0.1	74.8
0.01	76.1
0.001	74.5
0.0001	80.0
0.00001	79.9

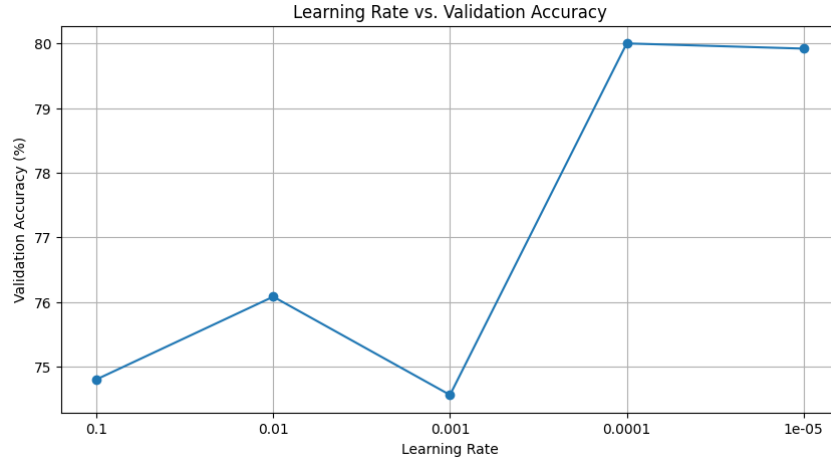


Figure 6: Validation accuracy for different learning rates.

2.7.2 Confusion Matrix for CNN (Figure 8)

For this confusion matrix, the CNN model was trained for 10 epochs with a learning rate of 0.0001.

3 Conclusion

Summarize findings, best performing model, and possible future improvements.

References

- [1] "Introduction to Convolution Neural Networks." GeeksforGeeks. Last updated on 3 Apr, 2025. <https://www.geeksforgeeks.org/introduction-convolution-neural-network/>
- [2] "Support Vector Machines". Scikit-learn documentation. Accessed on 30 May, 2025. <https://scikit-learn.org/stable/modules/svm.html>

Table 4: CNN Training Loss for Different Epochs

Epoch	Training Loss
1	0.73
2	0.52
3	0.42
4	0.34
5	0.30
6	0.24
7	0.20
8	0.17
9	0.14
10	0.13

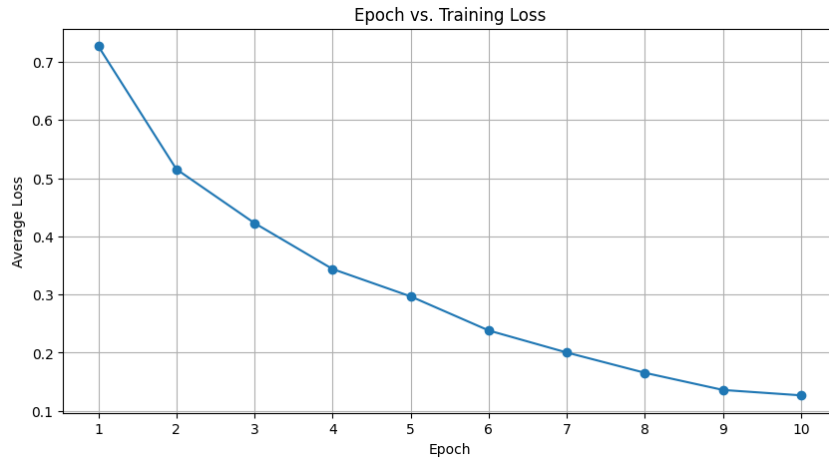


Figure 7: Training loss per epoch for the CNN model.

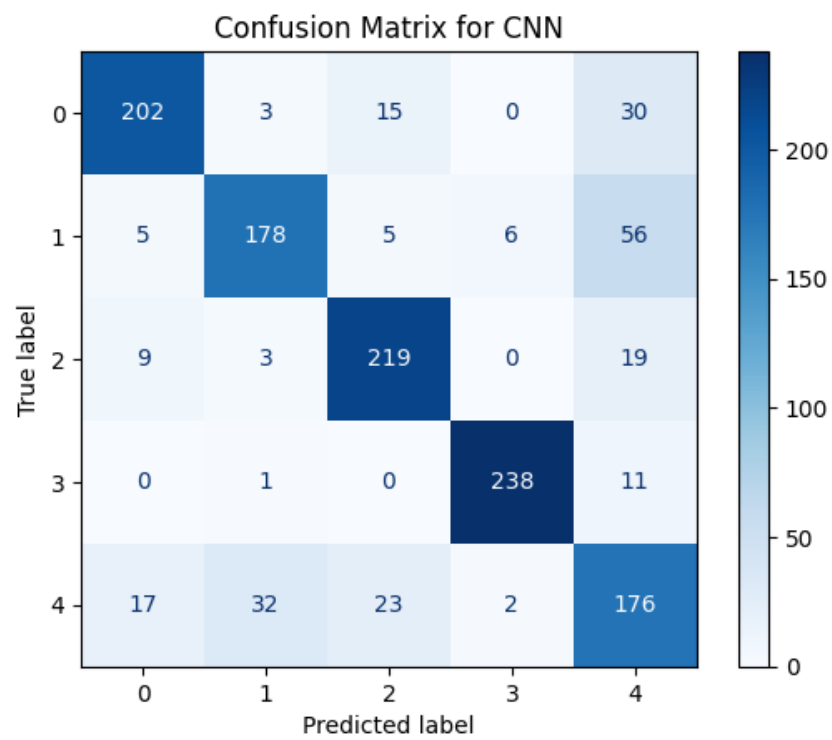


Figure 8: Confusion matrix for the CNN model.