Neural Network Project

Statistical Methods for Machine Learning
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1. Introduction

The aim of the project is to use neural networks for image binary classification of muffins and chihuahuas based on images provided by Kaggle dataset https://www.kaggle.com/datasets/samuelcortinhas/muffin-vs-chihuahua-image-classification.
The dataset comprises a total of images of muffins and Chihuahuas. Each image is labeled accordingly, indicating whether it belongs to the "muffin" or "Chihuahua" class. Images are in JPG format and they are splitted in train and test sets.
The main goal of this report is to experiment with various network architectures, consisting of three different configurations, as well as explore different training hyperparameters for the task of binary classification, and use of a 5-fold cross-validation technique to compute accurate risk estimates.

2. Neural Network

To create neural networks architectures, I have decided to use the three Convolutional neural networks with varying layers. I chose the CNNs because of their effectiveness in image classification tasks and their ability to capture spatial relationships within images. They ensure following points:

- Localized Feature Extraction: CNNs capture local patterns and features by using convolutional layers, allowing them to focus on important image characteristics.
- Parameter Sharing: CNNs share weights across different spatial locations, enabling them to generalize well and capture spatial invariances.
- Hierarchical Representation Learning: CNNs learn hierarchical representations by stacking convolutional layers, capturing increasingly complex and abstract features.
- Translation Invariance: Pooling layers reduce spatial dimensions, making CNNs robust to variations in object position, scale, and orientation.
- Scalability: CNNs can handle images of varying sizes and resolutions, making them adaptable to different image classification tasks.
- Availability of Pretrained Models: Pretrained CNN models provide learned features and facilitate transfer learning to new classification tasks.

These are the layers that are used in CNN:

- Convolutional layers - responsible for learning and extracting features from input images. They apply a set of filters to the input, performing convolution operations to detect local patterns and features. Each filter learns to detect specific visual patterns, such as edges or textures, in different regions of the image.
- MaxPooling layers - reduce the spatial dimensions of the feature maps produced by the convolutional layers. They divide the input into non-overlapping regions and keep only the maximum value within each region. MaxPooling helps to downsample the feature maps,

reducing computational complexity and providing translation invariance, making the network more robust to variations in object position.

- Flatten layer - is used to convert the multidimensional feature maps from the previous layers into a one-dimensional vector. It "flattens" the input, preserving the information and preparing it to be fed into the fully connected layers.
- Dense layers - also known as fully connected layers, are traditional neural network layers where each neuron is connected to every neuron in the previous layer. They map the learned features to the desired output classes. Dense layers enable the network to learn complex relationships between the features and the target classes.
- Output layer - the final layer of the network responsible for producing the predictions. In binary classification tasks, the output layer typically consists of two neurons with a softmax activation function. Softmax converts the output values into probabilities, representing the likelihood of each class, and allows the network to make a prediction based on the highest probability.

These layers work together to process the input images, extract features, reduce spatial dimensions, and make predictions based on the learned representations. The specific arrangement and combination of these layers contribute to the overall architecture and functionality of the CNN models.

3. Preprocessing

In the preprocessing phase of this project, I performed several steps to prepare the dataset for training the neural network models. First, the dataset is downloaded and extracted using Kaggle CLI commands. The dataset comprises 5917 images of muffins and Chihuahuas, which are going to be classified into two categories.

Upon loading the images, each image undergoes image processing steps. OpenCV is used to read the images, and the color space is converted from JPG to RGB to ensure consistency. Additionally, all images are resized to a uniform size of 32x32 pixels. The images are then stored in the 'x' array, while the corresponding labels are stored in the 'y' array. There is no need for split data in training and test set, because since there is cross validation, the whole dataset is used for both training and testing.

Normalization of the pixel values is performed by dividing them by 255.0. This step is crucial as it brings the pixel values within a consistent range of 0 to 1. Normalization helps in preventing any particular feature from dominating the learning process and allows for better convergence during training.

One-hot encoding is used to convert the class labels into a suitable format for the classification task. It involves representing each class as a binary vector, where the index corresponding to the class is set to 1 and the rest are set to 0. This encoding scheme is employed to facilitate the learning process and enable the neural network to interpret the categorical labels effectively.

4. Cross validation

I implemented cross-validation using the 5-fold cross validation with the KFold function from the scikit-learn library. For each fold, the data was split into training and validation sets. The training set was used to train the model, while the validation set was used to evaluate its performance. This process was repeated five times, with each fold serving as the validation set once. After training the model on the training set, it was evaluated on the validation set to compute zero-one loss.

The loss metric for the training part was calculated using the binary cross-entropy loss function. This loss function is commonly used for binary classification problems. It measures the dissimilarity between the predicted probabilities and the true labels. The lower the loss value, the better the model's predictions align with the ground truth. For the test part I used zero-one loss which is defined by 1 - accuracy. Accuracy is a metric computed to assess the model's classification performance. It represents the percentage of correctly classified samples out of all the samples.

The results from each fold, including the hyperparameters, validation loss, and validation accuracy, were stored for further analysis. The average cross-validated zero one loss was computed by taking the mean of the zero one loss from all folds.

5. Neural network architectures and hyperparameters tuning

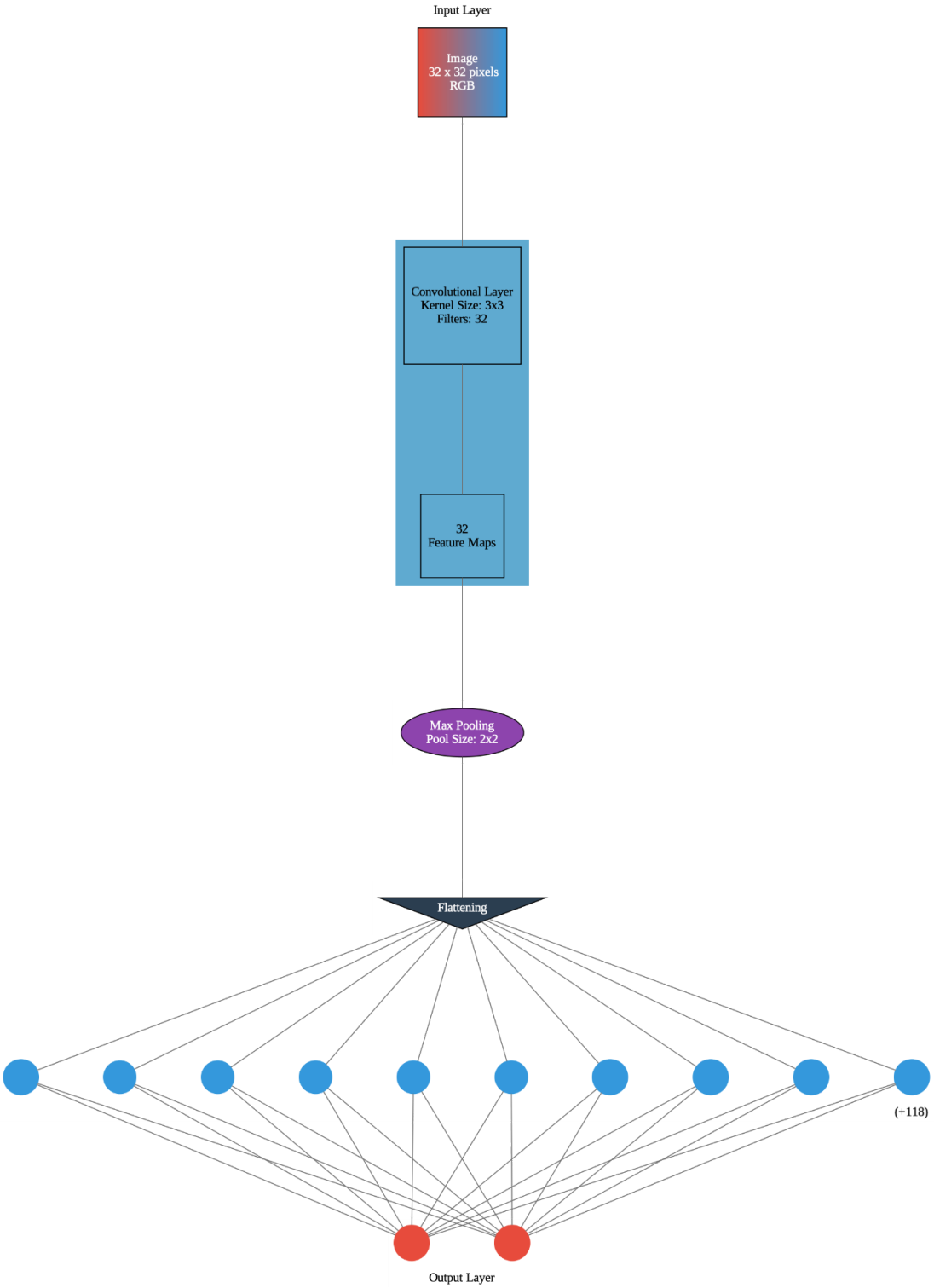
In the given code, three different neural architectures (model1, model2, model3) were implemented for image classification. Each architecture consists of a combination of convolutional layers, pooling layers, flatten layers, and dense layers.

5.1. Model 1

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 32)        896

 max_pooling2d (MaxPooling2D  (None, 15, 15, 32)       0
 )

 flatten (Flatten)           (None, 7200)              0

 dense (Dense)               (None, 128)               921728

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 922,882
Trainable params: 922,882
Non-trainable params: 0
```

Picture 1. Summary of model 1

- The architecture begins with a convolutional layer with 32 filters of size 3x3, using the ReLU activation function. It is followed by a max pooling layer with a pool size of 2x2, which reduces the spatial dimensions of the feature maps.
- Next, a flatten layer is used to convert the multidimensional feature maps into a 1D vector.
- A dense layer with 128 units and the ReLU activation function is added to introduce non-linearity and capture more complex patterns.
- The final layer consists of a dense layer with 2 units and the softmax activation function, which produces the probability distribution over the two classes (muffin and Chihuahua).



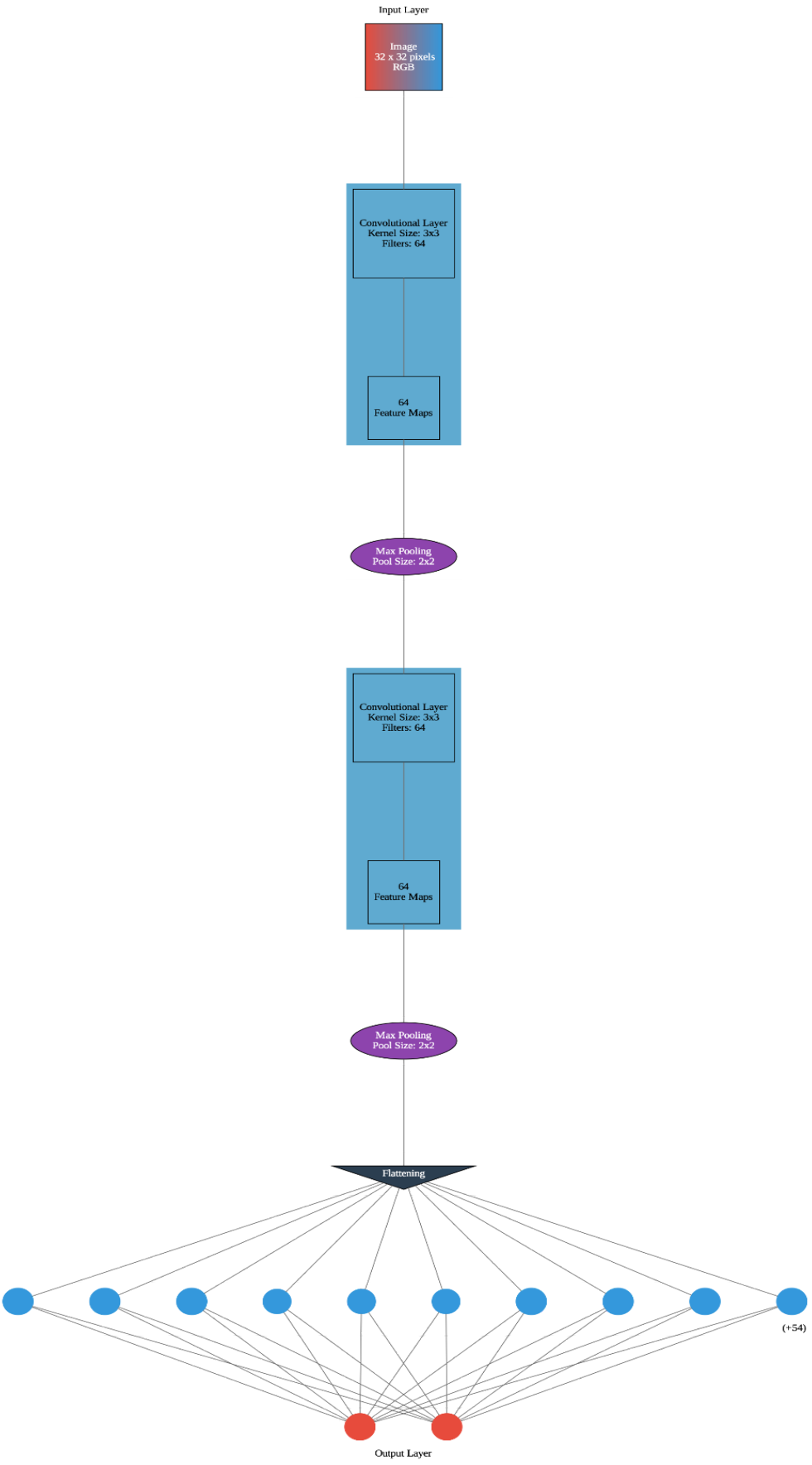
Picture 2. Visualization of model 1

5.2. Model 2

```
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)            (None, 30, 30, 64)        1792

 max_pooling2d_1 (MaxPooling  (None, 15, 15, 64)       0
 2D)

 conv2d_2 (Conv2D)            (None, 13, 13, 64)        36928

 max_pooling2d_2 (MaxPooling  (None, 6, 6, 64)         0
 2D)

 flatten_1 (Flatten)          (None, 2304)              0

 dense_2 (Dense)              (None, 64)                147520

 dense_3 (Dense)              (None, 2)                 130

=================================================================
Total params: 186,370
Trainable params: 186,370
Non-trainable params: 0
```

Picture 3. Summary of model 2

- The architecture is similar to model1 but with some differences. It starts with a convolutional layer with 64 filters of size 3x3, followed by a max pooling layer.
- Another convolutional layer with 64 filters is added, along with its corresponding max pooling layer.
- After the pooling layers, a flatten layer is used to transform the feature maps into a 1D vector.
- A dense layer with 64 units and the ReLU activation function is included.
- The final layer is a dense layer with 2 units and the softmax activation function.



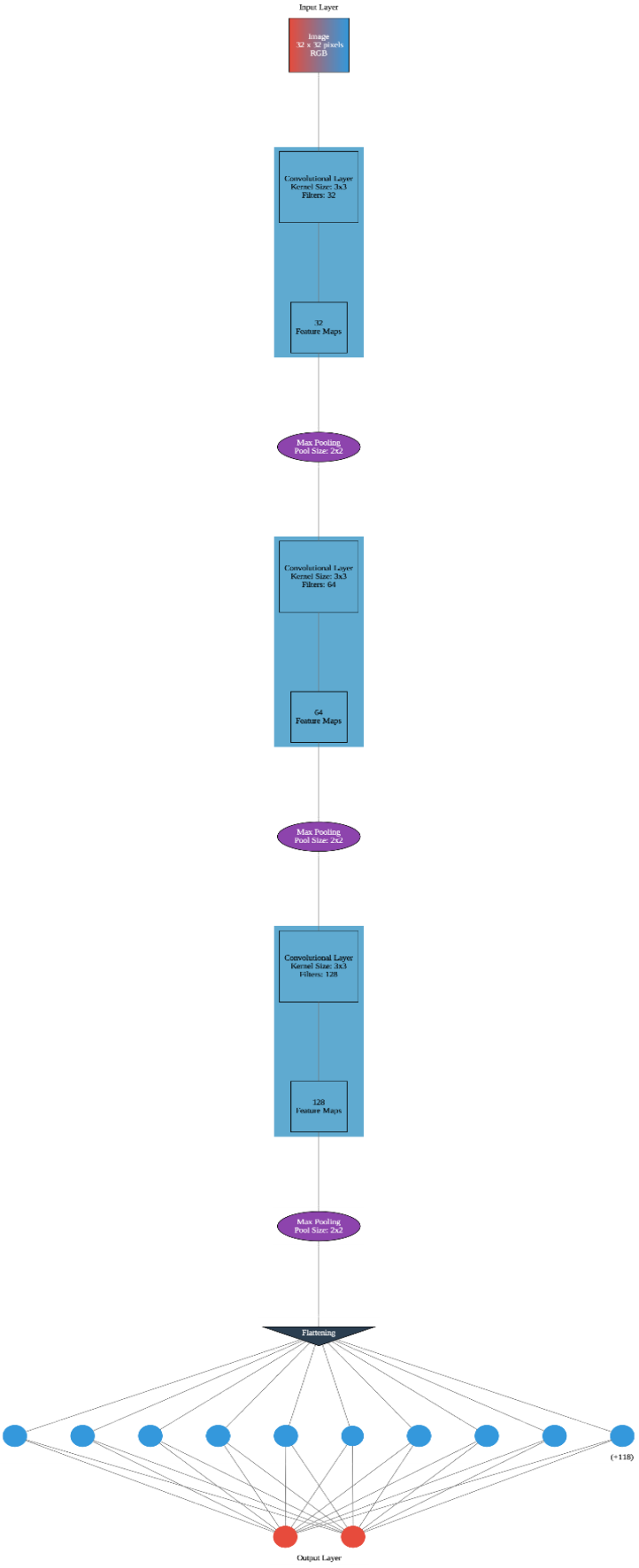
Picture 4. Visualization of model 2

5.3. Model 3

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_16 (Conv2D)          (None, 30, 30, 32)        896

 max_pooling2d_16 (MaxPoolin  (None, 15, 15, 32)       0
 g2D)

 conv2d_17 (Conv2D)          (None, 13, 13, 64)        18496

 max_pooling2d_17 (MaxPoolin  (None, 6, 6, 64)         0
 g2D)

 conv2d_18 (Conv2D)          (None, 4, 4, 128)         73856

 max_pooling2d_18 (MaxPoolin  (None, 2, 2, 128)        0
 g2D)

 flatten_7 (Flatten)         (None, 512)               0

 dense_14 (Dense)            (None, 128)               65664

 dense_15 (Dense)            (None, 2)                 258

=================================================================
Total params: 159,170
Trainable params: 159,170
Non-trainable params: 0
```

Picture 5. Summary of model 3

- The third architecture incorporates a deeper network structure compared to the previous two models. It begins with a convolutional layer with 32 filters of size 3x3, followed by a max pooling layer.
- Two additional convolutional layers with 64 and 128 filters, respectively, are included, each followed by a max pooling layer.
- Similar to the previous models, a flatten layer is used to convert the feature maps into a 1D vector.
- A dense layer with 128 units and the ReLU activation function is added.
- The final layer is a dense layer with 2 units and the softmax activation function.



Picture 6. Visualization of model 3

5.4. Hyperparameters

In my neural network models, I have utilized three important hyperparameters: learning rate, number of epochs, and batch size.

Learning Rate: The learning rate determines the step size at which the model adjusts its internal parameters during training. It controls how much the weights are updated in response to the calculated gradients. A higher learning rate may lead to faster convergence, but it can also cause overshooting. On the other hand, a lower learning rate may result in slower convergence or getting stuck in local optima.

Number of Epochs: An epoch represents one complete pass of the entire training dataset through the neural network. The number of epochs determines how many times the network will iterate over the training data. Too few epochs may result in underfitting, where the model fails to capture the patterns in the data. Conversely, too many epochs can lead to overfitting, where the model becomes overly specialized to the training data and performs poorly on new, unseen data.

Batch Size: The batch size defines the number of training examples processed in one forward and backward pass of the network. It affects the speed of training and the memory requirements. Larger batch sizes can improve training speed, but they may also require more memory. Smaller batch sizes allow for more frequent updates to the model's weights but can slow down training.

6. Results and analysis

To determine the best combination of hyperparameters, I decided to test all configurations with different models using the following values: learning_rate: 0.01, 0.001, 0.0001, batch_size: 16, 64, 128, and epochs: 8, 16, 24. For each configuration, I measured the zero-one loss as a mean of each zero-one loss of each fold and the execution time for one iteration of cross-validation. By systematically exploring these variations, I aimed to assess the impact of different learning rates, batch sizes, and numbers of epochs on the performance of the neural network.

6.1. Model 1

The results for model 1 are shown in table 1.

#	Epochs	Learning Rate	Batch Size	Cv zero-one loss	Training time for one cv iteration [s]
1	8	0,01	16	0,280051	39,458
2	16	0,01	16	0,361072	80,918
3	24	0,01	16	0,332619	133,972
4	8	0,01	64	0,374107	25,960
5	16	0,01	64	0,291734	65,019
6	24	0,01	64	0,221567	119,169

7	8	0,01	128	0,401332	31,839
8	16	0,01	128	0,241012	76,445
9	24	0,01	128	0,239984	79,262
10	8	0,001	16	0,200769	58,983
11	16	0,001	16	0,160557	135,678
12	24	0,001	16	0,194014	202,707
13	8	0,001	64	0,192672	40,272
14	16	0,001	64	0,216665	82,659
15	24	0,001	64	0,199768	137,893
16	8	0,001	128	0,200115	37,962
17	16	0,001	128	0,166477	79,450
18	24	0,001	128	0,193504	125,745
19	8	0,0001	16	0,163599	71,976
20	16	0,0001	16	0,159718	122,844
21	24	0,0001	16	0,205666	202,739
22	8	0,0001	64	0,196217	41,002
23	16	0,0001	64	0,174421	81,960
24	24	0,0001	64	0,193180	142,679
25	8	0,0001	128	0,246765	40,295
26	16	0,0001	128	0,187426	82,696
27	24	0,0001	128	0,195034	127,201

Table 1. Results for model 1

The best three hyperparameter configurations for minimizing zero-one loss are: 20, 11 and 19.

To examine the influence of different parameter values, I calculated the average zero-one loss and training time for each parameter and recorded the results in the following tables:

Learning Rate	Zero-One Loss	Time (s)
0.01	0.304831	72.449
0.001	0.191316	100.150
0.0001	0.191636	101.488

Table 2. Learning rate comparison for model 1

Lower learning rates (0.001 and 0.0001) yield lower zero-one loss values compared to a learning rate of 0.01. However, they also result in longer training times.

Batch Size	Zero-One Loss	Time (s)
16	0.228674	116.586
64	0.228926	81.846
128	0.230183	75.655

Table 3. Batch size comparison for model 1

The zero-one loss values are relatively similar across different batch sizes (16, 64, 128), with no significant differences. However, the best three results were for batch size 16. On the other hand, smaller batch sizes tend to require longer training times.

Number of Epochs	Zero-One Loss	Time (s)
8	0.250625	43.083
16	0.217676	89.741
24	0.219482	141.263

Table 4. Number of epochs comparison for model 1

Increasing the number of epochs generally leads to lower zero-one loss values, but the difference between 16 and 24 epochs is small. For a bigger number of epochs there are longer training times.

For this model after analyzing the results I draw the following conclusions. For lower learning rates (0.001 and 0.0001) yield lower zero-one loss values compared to a learning rate of 0.01. This indicates that a smaller learning rate allows the model to make more precise updates to the weights, resulting in better convergence and lower loss. However, lower learning rates also result in longer training times. For Batch Size the zero-one loss values are relatively similar across different batch sizes (16, 64, 128) in model 1, with no significant differences. This suggests that the choice of batch size does not have a substantial impact on the model's performance in this case. Smaller batch sizes tend to require longer training times due to the more frequent updates of the weights. However, the differences in training times between the different batch sizes in model 1 are not significant. Increasing the number of epochs generally leads to lower zero-one loss values, indicating improved performance as the model has more iterations to learn from the data. However, the difference in zero-one loss values between 16 and 24 epochs is small, suggesting that the additional epochs may not significantly contribute to further reducing the loss.With a higher number of epochs, the training time also increases.

Overall, in model 1, lower learning rates and a higher number of epochs tend to result in lower zero-one loss values. Batch size does not show a significant impact on the zero-one loss in this case.

6.2. Model 2

For model 2 I got following results:

#	Epochs	Learning Rate	Batch Size	Cv zero-one loss	Training time for one cv iteration [s]
1	8	0,01	16	0,400137	80,705
2	16	0,01	16	0,278680	181,931
3	24	0,01	16	0,436821	256,928
4	8	0,01	64	0,214272	75,995
5	16	0,01	64	0,214141	139,534
6	24	0,01	64	0,227998	251,315
7	8	0,01	128	0,269589	72,010
8	16	0,01	128	0,192324	139,978
9	24	0,01	128	0,204838	201,631
10	8	0,001	16	0,131824	133,696
11	16	0,001	16	0,139940	226,476
12	24	0,001	16	0,164446	334,735
13	8	0,001	64	0,125916	105,643
14	16	0,001	64	0,144163	185,995
15	24	0,001	64	0,127095	251,094
16	8	0,001	128	0,169513	77,149
17	16	0,001	128	0,162917	191,693
18	24	0,001	128	0,127765	262,739
19	8	0,0001	16	0,175948	142,715
20	16	0,0001	16	0,167493	263,074
21	24	0,0001	16	0,157505	373,899
22	8	0,0001	64	0,258438	142,834
23	16	0,0001	64	0,159382	197,884
24	24	0,0001	64	0,194030	314,408
25	8	0,0001	128	0,268900	133,134
26	16	0,0001	128	0,226808	197,946
27	24	0,0001	128	0,181512	303,355

Table 6. Results for model 2

The best three hyperparameter configurations for minimizing zero-one loss are: 13, 15 and 18. For model 2 I also calculated following average values:

Learning Rate	Zero-One Loss	Time (s)
0.01	0.270978	155.559
0.001	0.143731	196.580

0.0001	0.198891	229.917

Table 7. Learning rate comparison for model 2

A learning rate of 0.001 yields the lowest zero-one loss value, indicating better predictive performance compared to the other learning rates. For the decreasing number of learning rates, the training time is increasing.

Batch Size	Zero-One Loss	Time (s)
16	0.228088	221.573
64	0.185048	184.967
128	0.200463	175.515

Table 8. Batch size comparison for model 2

The batch size 64 achieves the lowest average of zero-one loss. With the increasing number of batch sizes, the time is decreasing.

Number of Epochs	Zero-One Loss	Time (s)
8	0.223837	107.098
16	0.183411	199.506
24	0.202446	283.345

Table 9. Number of epochs comparison for model 2

The best given average value for zero-one loss is for the number of 16. Naturally, for more epochs the training time is longer.

Based on the results for model 2, I draw the following conclusions regarding the impact of learning rate, batch size, and number of epochs on the zero-one loss and training time.
Among the three tested learning rates (0.01, 0.001, 0.0001) in model 2, a learning rate of 0.001 yields the lowest zero-one loss value. This indicates that a smaller learning rate allows the model to make more precise updates to the weights and results in better predictive performance. The training time increases as the learning rate decreases. This is because smaller learning rates require more iterations to converge, leading to longer training times. Model 2 shows that a batch size of 64 achieves the lowest average zero-one loss. This suggests that a moderate batch size can effectively capture the patterns in the data and lead to better predictive performance. Interestingly, the training time is relatively similar for batch sizes 64 and 128 in model 2. This may be due to the specific characteristics of the dataset or the model architecture used. Among the tested number of epochs in model 2, the lowest average zero-one loss value is achieved with 16 epochs. This indicates that increasing the number of epochs beyond 16 does not significantly contribute to further reducing the loss. As expected, the training time increases as the number of epochs increases. More epochs require more iterations to train the model, resulting in longer training times.

In summary, for model 2, a learning rate of 0.001, a batch size of 64, and around 16 epochs appear to be the optimal hyperparameter configurations for minimizing zero-one loss. These configurations lead to better predictive performance while also managing the training time efficiently.

6.3. Model 3

For model 3 these are the calculated values:

#	Epochs	Learning Rate	Batch Size	Cv zero-one loss	Training time for one cv iteration [s]
1	8	0,01	16	0,859509725	75,79416437
2	16	0,01	16	0,575114227	192,8911489
3	24	0,01	16	0,708199495	254,7099952
4	8	0,01	64	0,458120966	77,18917809
5	16	0,01	64	0,369377553	142,1593581
6	24	0,01	64	0,238973439	242,7976195
7	8	0,01	128	0,247248328	75,85853934
8	16	0,01	128	0,174251497	141,0171684
9	24	0,01	128	0,192165756	201,6922361
10	8	0,001	16	0,208200490	137,04847
11	16	0,001	16	0,168173838	263,3265848
12	24	0,001	16	0,139602852	383,139579
13	8	0,001	64	0,201311231	112,7271017
14	16	0,001	64	0,139256859	203,1484431
15	24	0,001	64	0,137404335	323,3699697
16	8	0,001	128	0,207013774	81,84665523
17	16	0,001	128	0,152251077	183,1302708
18	24	0,001	128	0,131996775	257,1092425
19	8	0,0001	16	0,188935876	143,0799482
20	16	0,0001	16	0,154290366	263,2899737
21	24	0,0001	16	0,141807067	380,1441409
22	8	0,0001	64	0,223272252	143,2119673
23	16	0,0001	64	0,257241523	189,5568923
24	24	0,0001	64	0,160893631	240,9050732
25	8	0,0001	128	0,219712245	88,68867693
26	16	0,0001	128	0,195377505	154,5108853
27	24	0,0001	128	0,146094689	219,4244633

Table 10. Results for model 3

The best three hyperparameter configurations for minimizing zero-one loss are: 18, 15 and 14.

The average values for model 3 are:

Learning Rate	Zero-One Loss	Time (s)
0.01	0.424773	156.012
0.001	0.165023	216.094
0.0001	0.187514	202.535

Table 11. Learning rate comparison for model 3

A learning rate of 0.001 achieves the lowest zero-one loss value, indicating better predictive performance compared to the other learning rates. It also exhibits a shorter training time compared to the learning rate of 0.0001.

Batch Size	Zero-One Loss	Time (s)
16	0.349315	232.603
64	0.242872	186.118
128	0.185124	155.920

Table 12. Batch size comparison for model 3

Batch size 128 ensures the lowest training error with the lowest training time.

Number of Epochs	Zero-One Loss	Time (s)
8	0.312592	103.938
16	0.242815	192.559
24	0.221904	278.144

Table 13. Number of epochs comparison for model 3

In this model with a high number of epochs the zero-one loss is decreasing and time is increasing.

For this model I draw the following conclusions. Among the three tested learning rates (0.01, 0.001, 0.0001) in model 3, a learning rate of 0.001 achieves the lowest zero-one loss value. This suggests that a smaller learning rate allows the model to make more precise updates to the weights and improve the predictive performance. The training time for the model is shorter with a learning rate of 0.001 compared to 0.0001, indicating that a moderate learning rate can achieve better performance without significantly increasing the training time. Model 3 shows that a batch size of 128 yields the lowest average zero-one loss. This indicates that using larger batches helps the model capture the data patterns more effectively and leads to improved predictive performance. The training time decreases as the batch size decreases. This is because smaller batch sizes require more iterations to process the

entire dataset, leading to longer training times. Among the tested number of epochs in model 3, increasing the number of epochs generally leads to lower zero-one loss values. This suggests that allowing the model to train for more epochs improves its ability to learn and make better predictions. The training time increases as the number of epochs increases. This is expected since more epochs require more iterations to train the model, resulting in longer training times.
In summary, for model 3, a learning rate of 0.001, a batch size of 128, and around 24 epochs appear to be the optimal hyperparameter configurations for minimizing zero-one loss. These configurations lead to better predictive performance while managing the training time reasonably well.

6.4. Model comparison

By comparing the results among the three models and analyzing the tables, the following general observations can be made:
Learning Rate:

- Across all models, a learning rate of 0.001 achieved the lowest zero-one loss values compared to 0.01 and 0.0001. This indicates that a moderate learning rate allows the model to find a better balance between convergence and avoiding getting stuck in local optima.
- The training times for different learning rates varied among the models but did not follow a consistent pattern. Therefore, the impact of learning rate on training time seems to be model-dependent.

Batch Size:

- There is no clear trend in the zero-one loss values based on the batch size. The performance varies across the models and depends on the specific combination of other hyperparameters.
- The training times tend to decrease as the batch size increases. This can be attributed to the more efficient parallel processing of larger batches.

Number of Epochs:

- The zero-one loss values generally decrease as the number of epochs increases. This indicates that allowing the model to train for more iterations improves its performance and ability to learn complex patterns in the data.
- However, longer training times are associated with a higher number of epochs. This is expected as more epochs require more iterations of forward and backward passes during training.

To compare performance with different models I calculated average loss and training time.

Model	1	2	3
Zero-one loss	0,217346	0,197010	0,259104
Time (s)	92,185	198,377	191,547

Table 14. Average values of loss and training time for 3 models

- Model 2 achieved the lowest zero-one loss values across different hyperparameter settings and the best overall result with loss equals to 0,125916.
- Model 3 also performed well, achieving competitive results with a slightly higher zero-one loss than Model 2.

- Model 1 generally had higher zero-one loss values compared to the other two models. However, it still demonstrated reasonable performance and could potentially benefit from further optimization.

Overall, the choice of the model architecture plays a crucial role in the performance of the neural network. The results suggest that Model 2 might be the most effective and efficient choice among the three models tested.

6.5. Image size

All models were tested on images resized to a dimension of 32x32 pixels. However, I also wanted to explore the impact of scaling the images to a larger size, specifically 64x64 pixels to check if scaling the images to a larger size improves the models' classification performance. To investigate this, I decided to select the hyperparameters and model configuration that yielded the lowest zero-one loss values in the previous experiments: model2, learning rate = 0,001 and batch size = 64. I run code for 8, 16 and 24 epochs. Results are in the following table.

#	Epochs	Learning Rate	Batch Size	Cv zero-one loss	Training time for one cv iteration [s]
1	8	0,001	64	0,142137	261,719
2	16	0,001	64	0,120339	540,888
3	24	0,001	64	0,135884	791,965

Table 15. Results for 64x64 image

Results are quite better than for 32x32 images, but considering training time for one iteration, it is not worth using a bigger size of images for this model.

7. Reproducibility and Code Availability

In this project, the code was developed using Google Colab, a cloud-based platform that allows for easy sharing and collaboration on Jupyter notebooks. Google Colab provides a convenient environment for executing code, as it offers pre-installed libraries and resources necessary for machine learning tasks. Additionally, the only requirement to run the code is to have Kaggle credentials for downloading the dataset. By providing these credentials, other researchers can readily reproduce experiments and obtain the same dataset used in the project.

I declare that this material, which I now submit for assessment, is entirely my/our own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my/our work. I understand that plagiarism, collusion, and copying are grave and serious offences in the university and accept the penalties that would be imposed should I engage in plagiarism, collusion or copying. This assignment, or any part of it, has not been previously submitted by me/us or any other person for assessment on this or any other course of study.