

# Image Recognition for Prediction of Forest Health

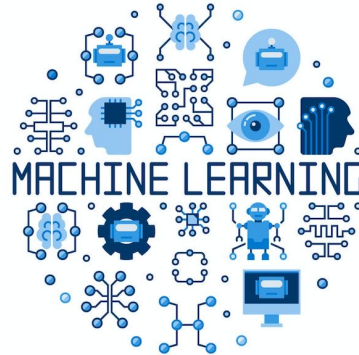


# Outline

- Introduction
- Overview
- Data Preprocessing
- Principal Component Analysis
- Classification models:
  - Support Vector Machine
  - K-Nearest Neighbour
  - Convolutional Neural Network
- Comparative Study
- Conclusion
- References

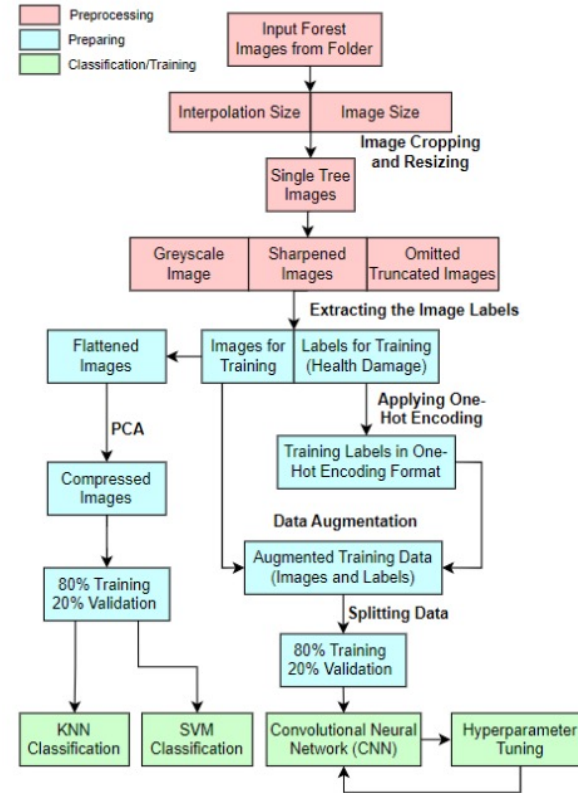
# Introduction

- Image Classification is one of the application of machine learning
- **Objective of project:** To predict the forest health of given images using different machine learning algorithms



# Overview

- Stage 1: Data Pre-processing
- Stage 2: Data Preparing
- Stage 3: Training and Classification

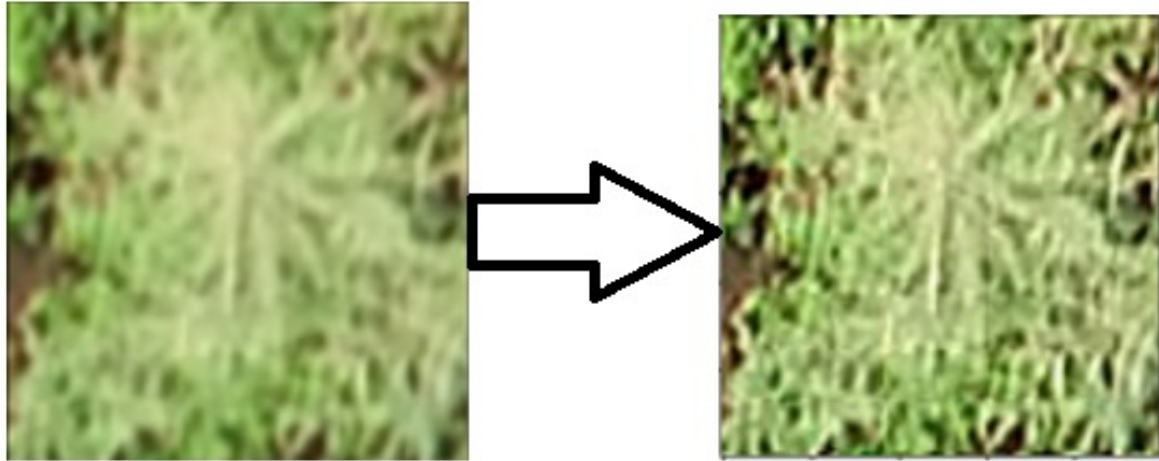




# Data Preprocessing - Part 1



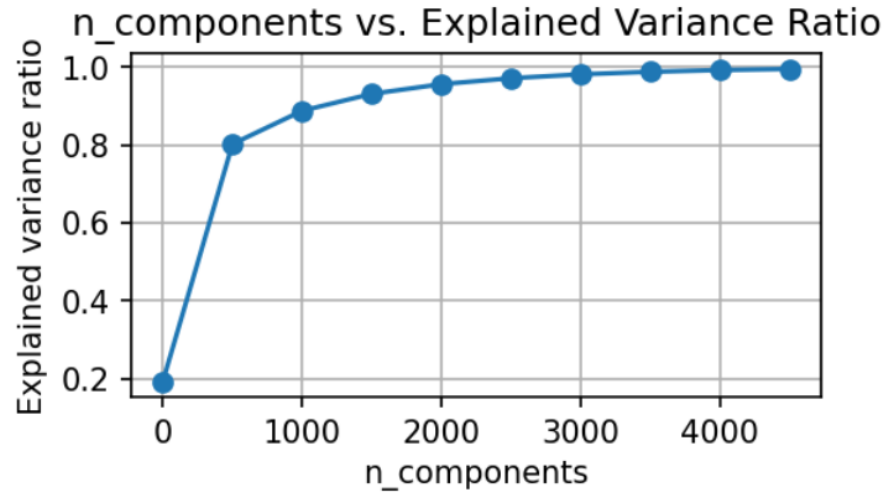
# Data Preprocessing - Part 2



# PCA – Implementation



# PCA – Results



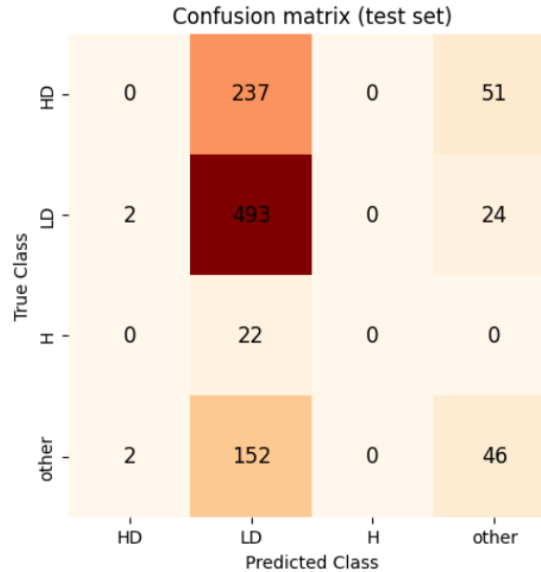


# SVM - Implementation

- Library: *sklearn.svm.SVC*
- Methods for multiclass: ovo, ovr
- Class\_weight = balanced
- 500 Principal Components
- 80% explained variance ratio
- 95% compression

# SVM - Results

- without regularization
- Validation accuracy: 53,8%
- Test accuracy: 52,7%



SVM is not fitted to the features

# SVM - Results

- with regularization
- Validation accuracy: 53,6%
- Test accuracy: 44,5%

Confusion matrix (test set)

	HD	LD	H	other
HD	84	100	34	70
LD	57	306	114	42
H	1	7	14	0
other	29	41	65	65
	HD	LD	H	other

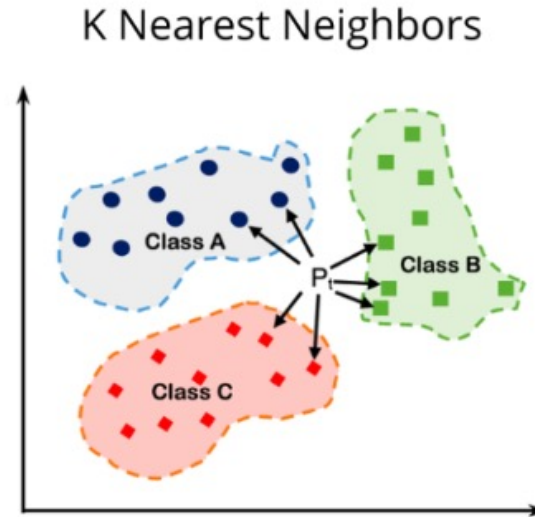
True Class

Predicted Class

SVM is fitted to the features, but overall bad performances -> information loss

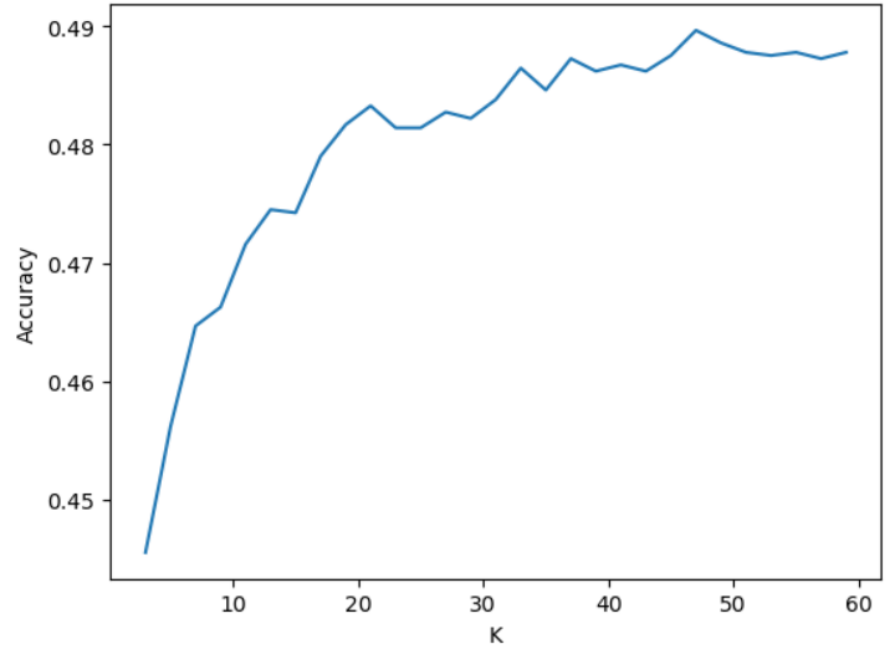
# KNN - Implementation

- Libraries used: `sklearn.model_selection`, `sklearn.neighbors`, and `sklearn.metrics`
- 2 PCA
- 24.5% explained variance
- 99.98% compression



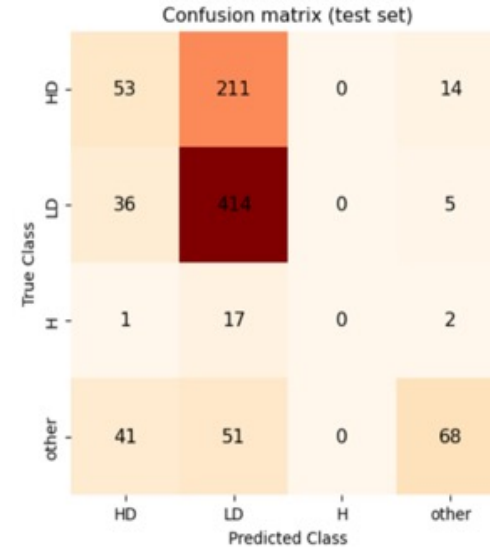
# KNN - Accuracy Graph

- Graph of Accuracy (%) vs K nearest neighbours
- Accuracy stops improving after at around K = 40 (Optimal K value = 40)



# KNN - Results

- Most predicted classes are Low Damage (LD), followed by High Damage (HD).
- No prediction for Healthy (H)
- Struggles to predict HD and Other



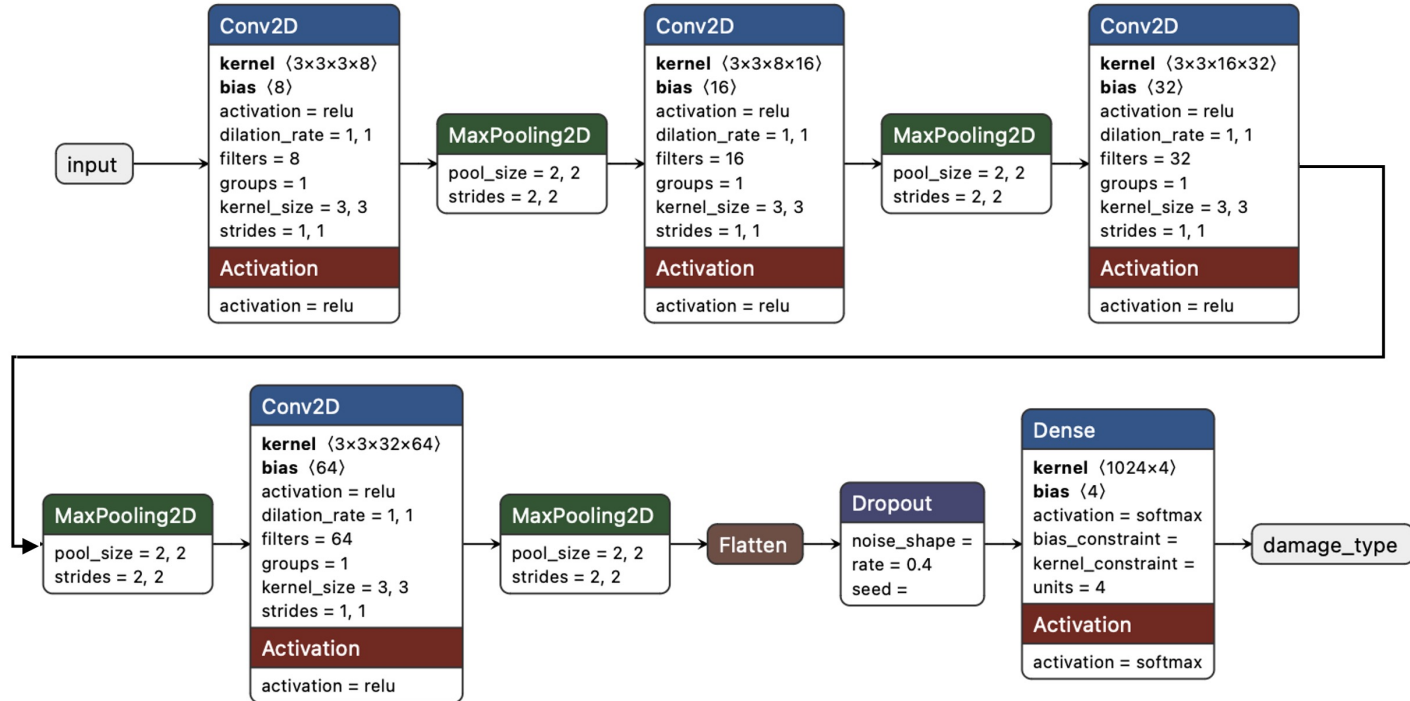


# CNN - Implementation

- Library: *tensorflow.keras*
- Functional API
- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- During training:
  - Custom Model Checkpoint
  - Shuffling of the training data



# CNN - Architecture



# CNN - Hyperparameter Tuning (1)

- Method - **Grid search**
- **Structural** hyper-parameters: number of layers and filters/neurons, dropout rate.
- **Training** hyper-parameters: learning rate, batch size, number of epochs.
- **Pre-processing** parameters: image size, omitting truncated images, interpolation method for resizing

# CNN - Hyperparameter Tuning (2)

Learning Rate	Dropout Rate	Batch Size	Epochs	Image Size	Omit Truncated	Interpolation Type	Sharpen Image
0.0003	0.4	32	50	100 x 100	No	Cubic	Yes

- Optimal Hyper-parameters chosen to train the CNN after grid search

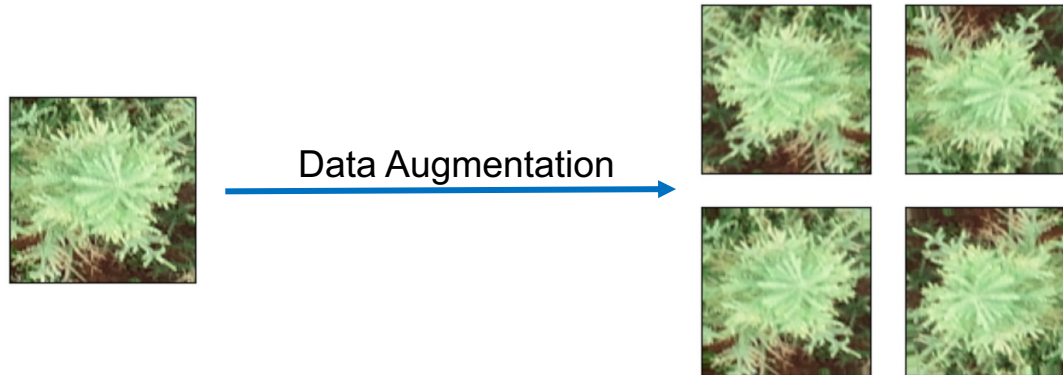
# CNN - Analyzing the Training Data

Class (Damage Type)	HD	LD	H	other
# of training images	3,215	12,707	1,659	2,941

- Clearly the data is unbalanced!
- Solution => Data Augmentation

# CNN - Data Augmentation

- Generate new images from the original ones
- *ImageDataGenerator* class in *tensorflow.keras.preprocessing.image*
- Rotate and Flip!
- Avoiding aggressive augmentation

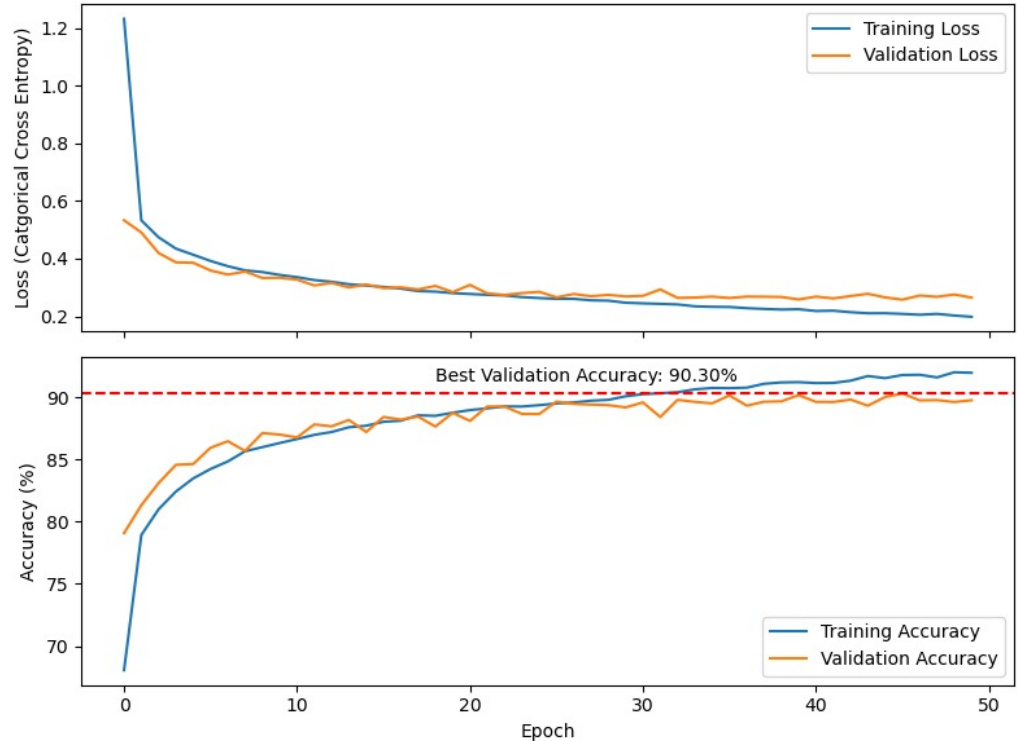




# CNN - Training

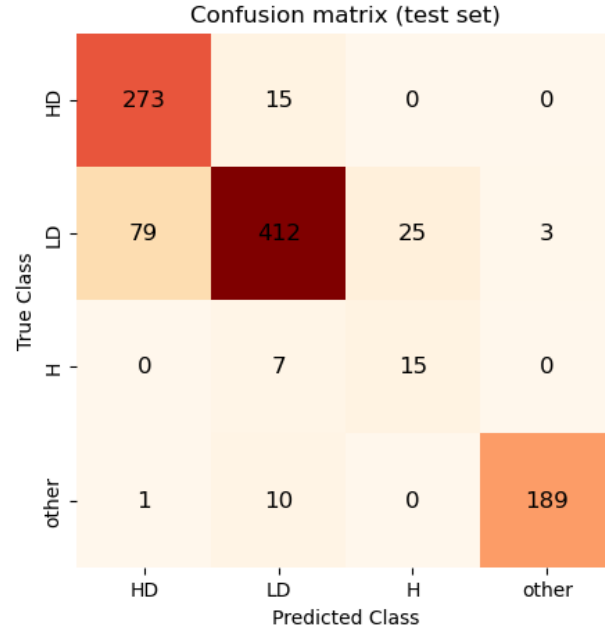
- Training/Validation loss and accuracy for 50 epochs using balanced and augmented data:

Best Validation Accuracy: 90.3%



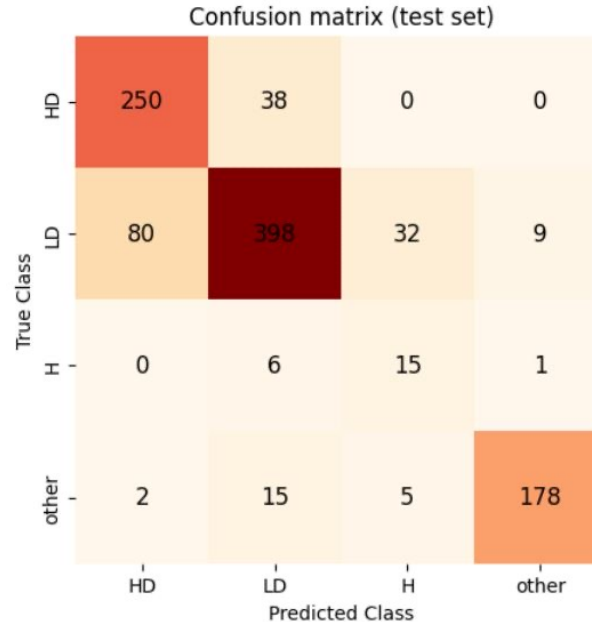
# CNN - Results

- Trained with balanced and augmented data
- Test Accuracy: 87.3% (unseen data)



# CNN - Results

- Trained using weighted sampling
- Class Weights:
  - HD: 1.8
  - LD: 1
  - H: 10
  - other: 3
- Test accuracy: 81%



# Comparative Study

Model	K-NN	SVM	CNN
Validation Accuracy (%)	53	44.5	90.3
Generalization	Bad	Moderate	Very Good
Model Complexity	Low	Low	High

# Conclusion

- Employing ML Classification for forest image recognition is very efficient
- Pre-processing and preparing training data is crucial
- Data should be balanced, diverse, extensive, and representative of actual problem
- CNNs are the most reliable for image classification
- Hyper-parameter tuning is challenging but necessary

# References

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