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Research on hyperparameters for the classification of ultrasonic signals

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Contents

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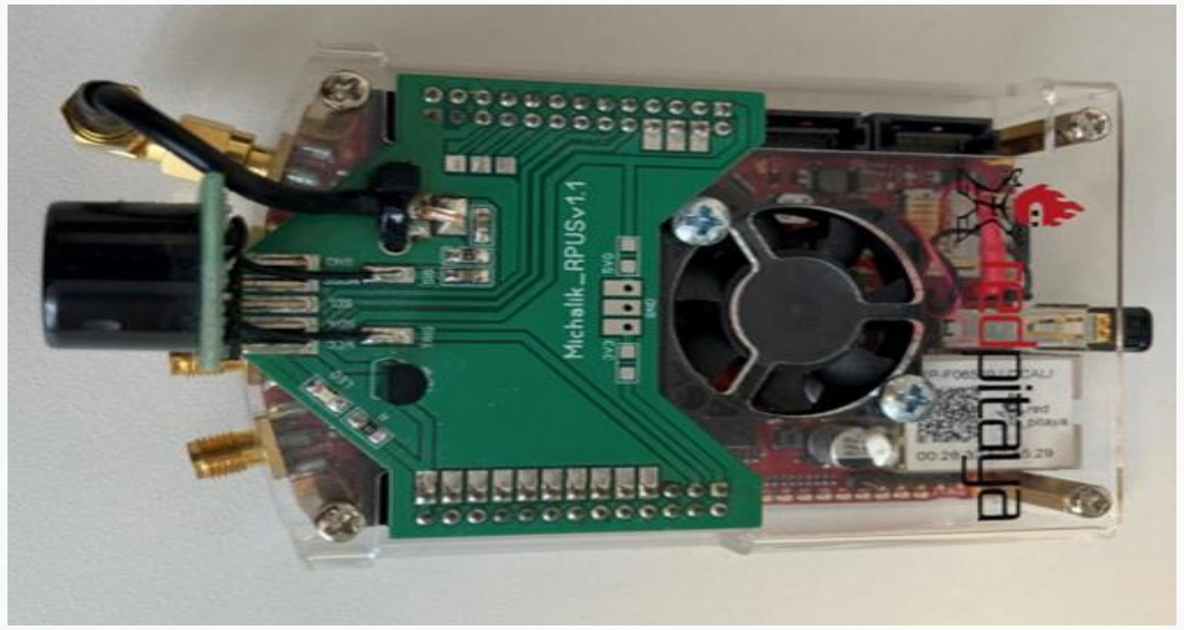
Introduction

The objective of the study is to examine how different machine learning model for ultrasonic signal classification are affected by hyperparameter tuning. The study analyses how hyperparameter adjustment can increase the models' capacity to distinguish between different materials based on ultrasonic waves the reflect.

Methodology

Sensor System and Red Pitaya Measurement Board



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Methodology

Ultrasonic Object Differentiation

1. Time-of-Flight (ToF) Principle
2. Pulse-Echo Method
3. Phase Shift Measurement
4. Multi-Echo Detection
5. Dual-Transducer Systems
6. Temperature Compensation

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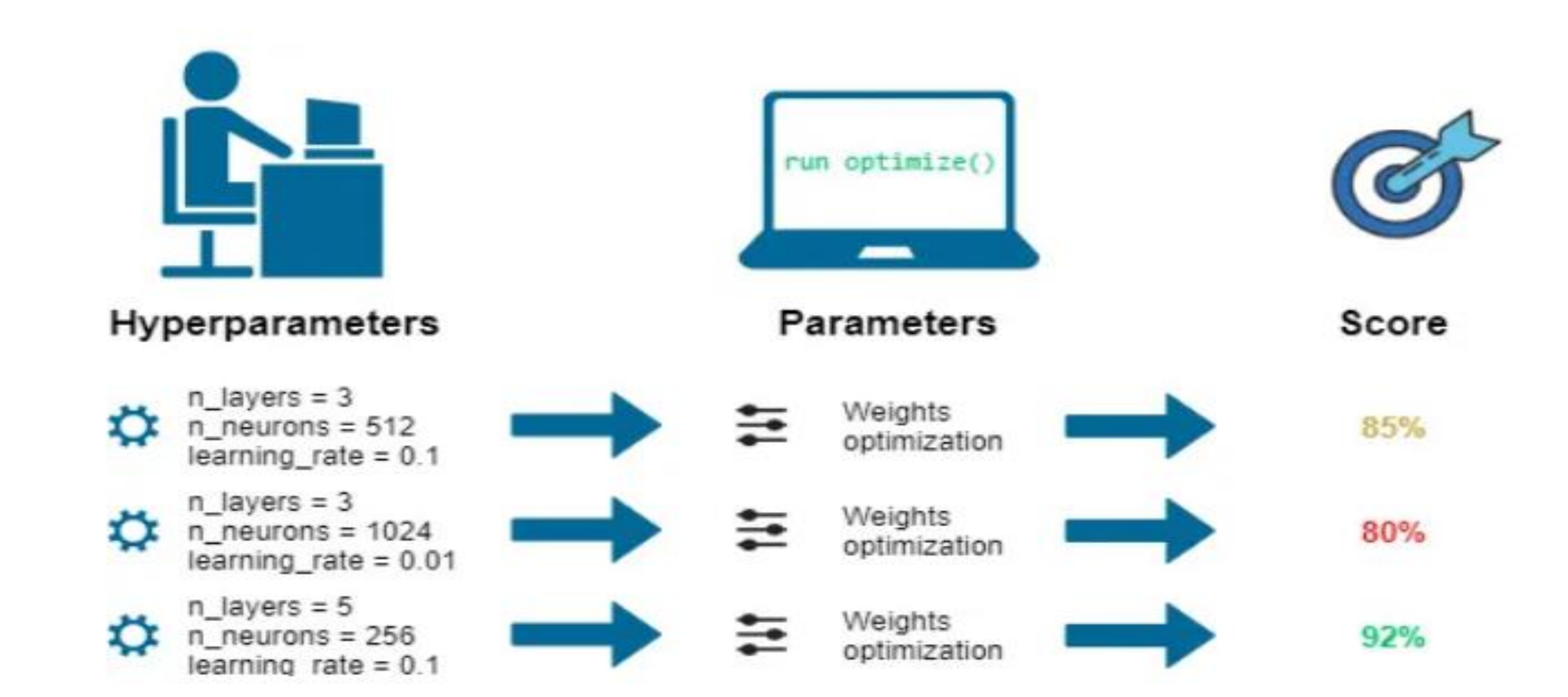
Methodology

Hyperparameter Optimization

•**Hyperparameters** = are all the parameters which can be arbitrarily set by the user before starting training (eg. number of estimators in Random Forest).



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Methodology

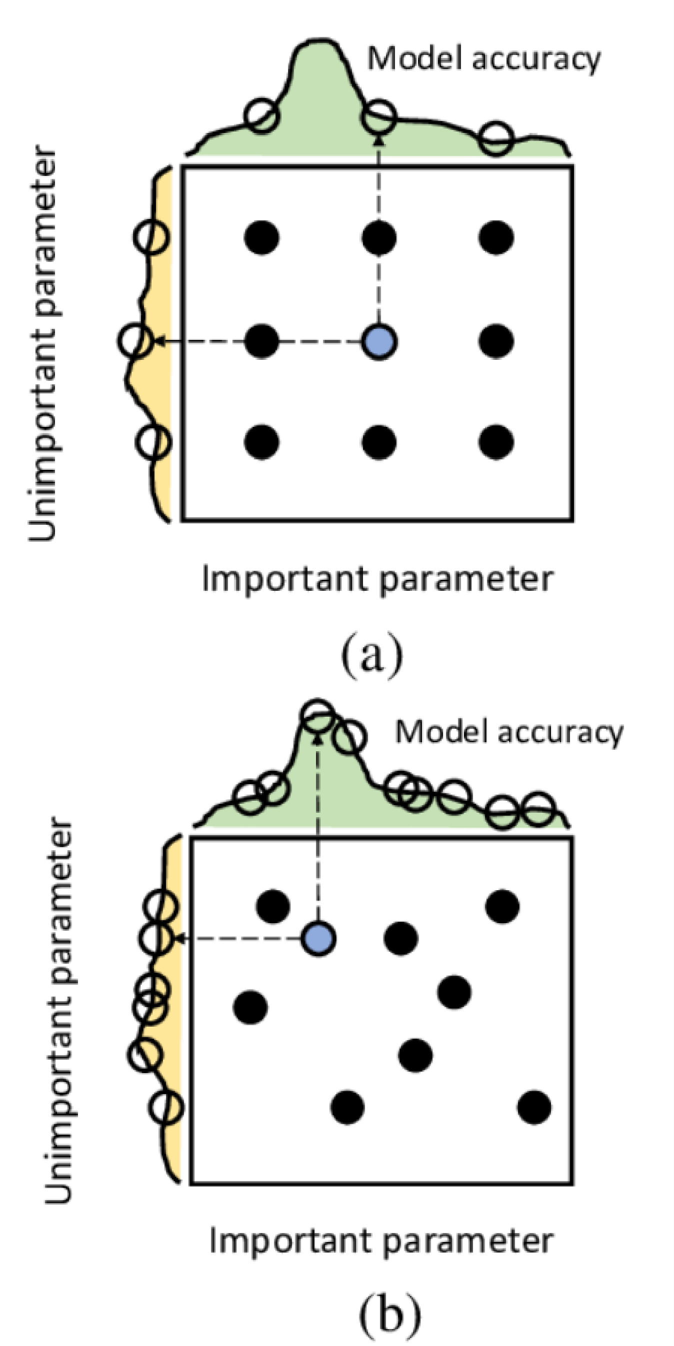
Hyperparameter Optimization Techniques

Grid Search:

This approach is a brute-force technique that searches over the hyperparameter space of the learning algorithm in a predetermined subset. To speed up the search, the technique can be parallelized among several models with various configurations.

Random Search:

This approach chooses random values from the hyperparameter subset independently. By navigating the grid of hyperparameters randomly, one can obtain a similar performance as a full grid search. However, this approach is surprisingly easy and effective.



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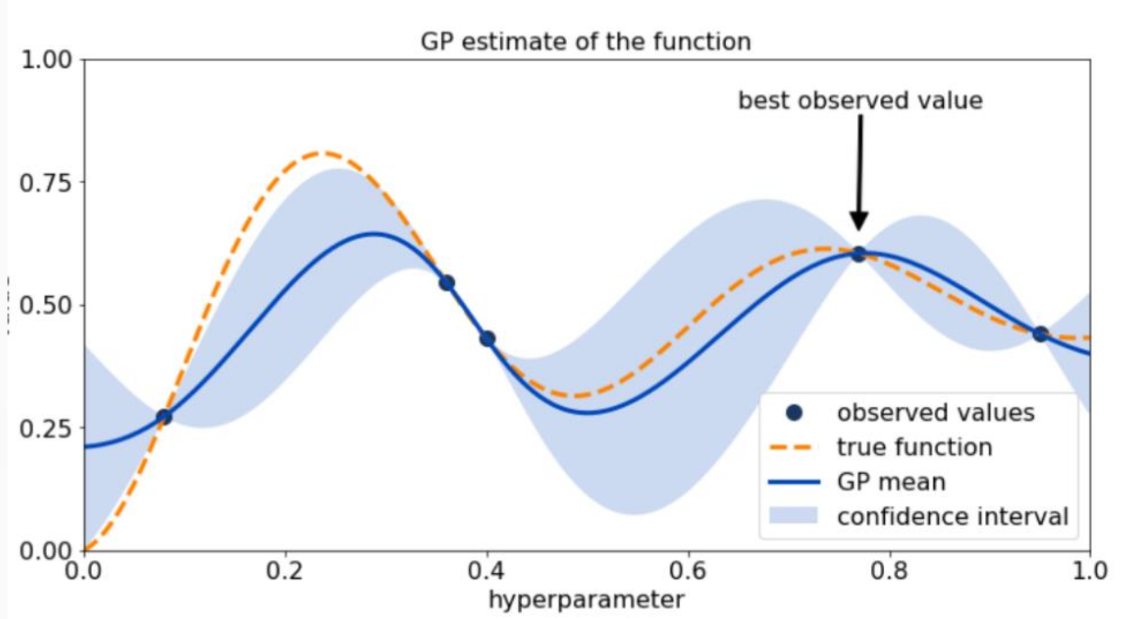
Methodology

Hyperparameter Optimization Techniques

Bayesian optimization:

This approach builds a surrogate model based on a random selection of hyperparameters and forecasts the performance of more combinations. To reduce the objective function, it strikes a balance between exploration and exploitation



Hyperband Search: exploitation Hyperband efficiently explores many hyperparameter configurations by allocating limited resources initially and increasing them for top performing ones. It balances exploration of a wide range of options with a focus on the best configurations, optimizing both time and performance.

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Data Preprocessing for Model Training

Windowing to Reduce Spectral Leakage

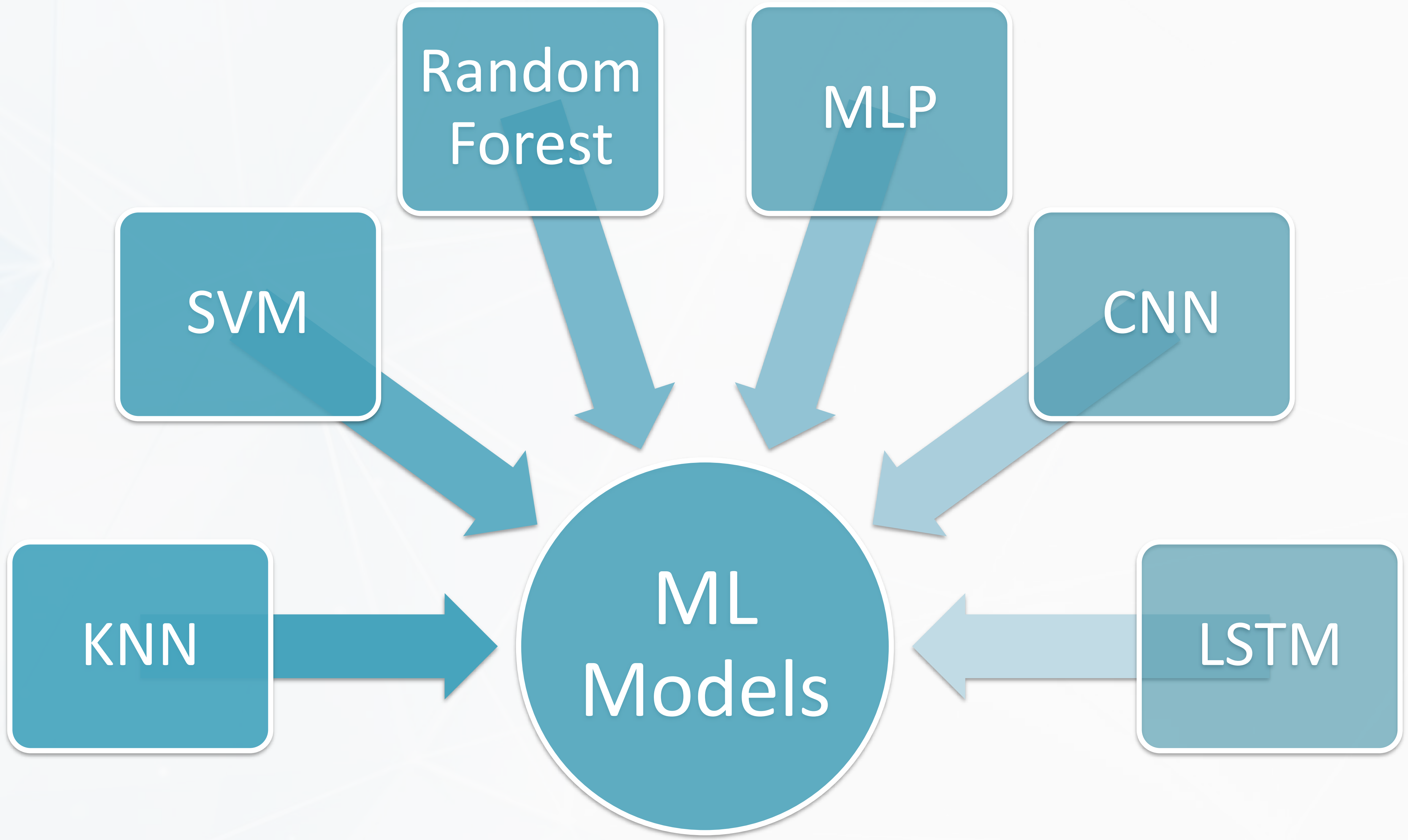
Fourier Transform (FFT) for frequency analysis of signals

Extracting SINAD, peak (count, position) , and autocorrelation

Extracted Features:

	sinad	peak_count	peak_position	autocorr_max	label
0	16.888277	2	85	8.770884e+08	aluminum
1	15.771295	3	5	8.747460e+08	aluminum
2	16.307615	2	85	9.741237e+08	aluminum
3	16.905421	4	1	8.861499e+08	aluminum
4	16.266501	2	85	9.645380e+08	aluminum

Machine learning Models



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Results

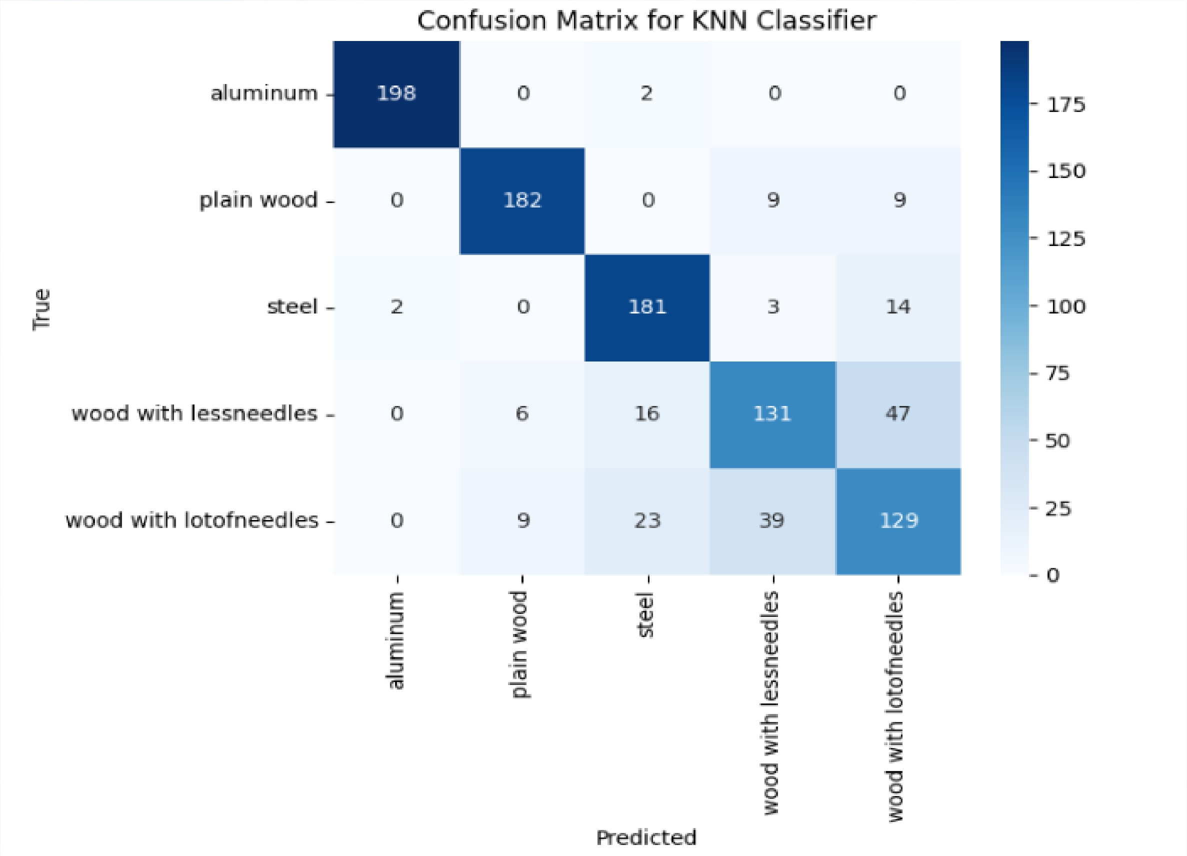
K-Nearest Neighbours (KNN)

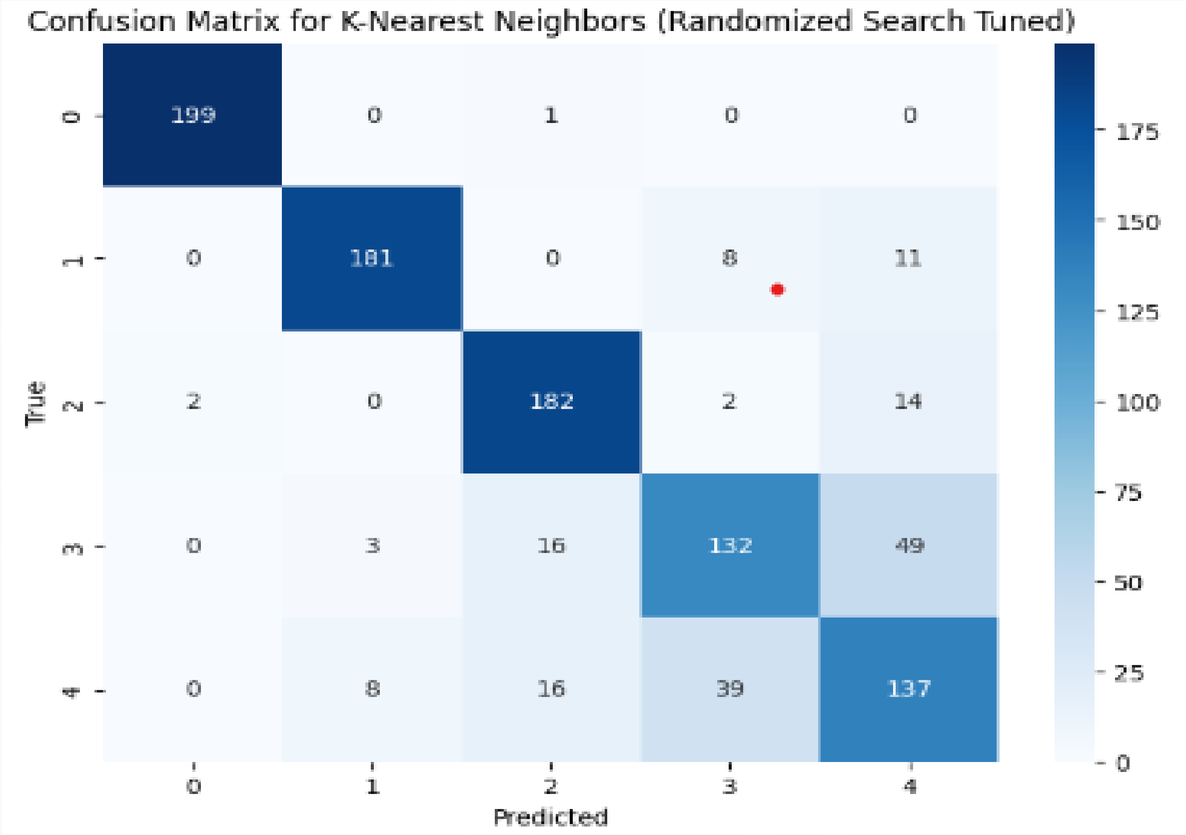
Classification Report for KNN Classifier:

	precision	recall	f1-score	support
aluminum	0.99	0.99	0.99	200
plain wood	0.92	0.91	0.92	200
steel	0.82	0.91	0.86	200
wood with lessneedles	0.72	0.66	0.69	200
wood with lotofneedles	0.65	0.65	0.65	200
accuracy			0.82	1000
macro avg	0.82	0.82	0.82	1000
weighted avg	0.82	0.82	0.82	1000

Classification Report for K-Nearest Neighbors (Randomized Search Tuned):

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.94	0.91	0.92	200
2	0.85	0.91	0.88	200
3	0.73	0.66	0.69	200
4	0.65	0.69	0.67	200
accuracy			0.83	1000
macro avg	0.83	0.83	0.83	1000
weighted avg	0.83	0.83	0.83	1000





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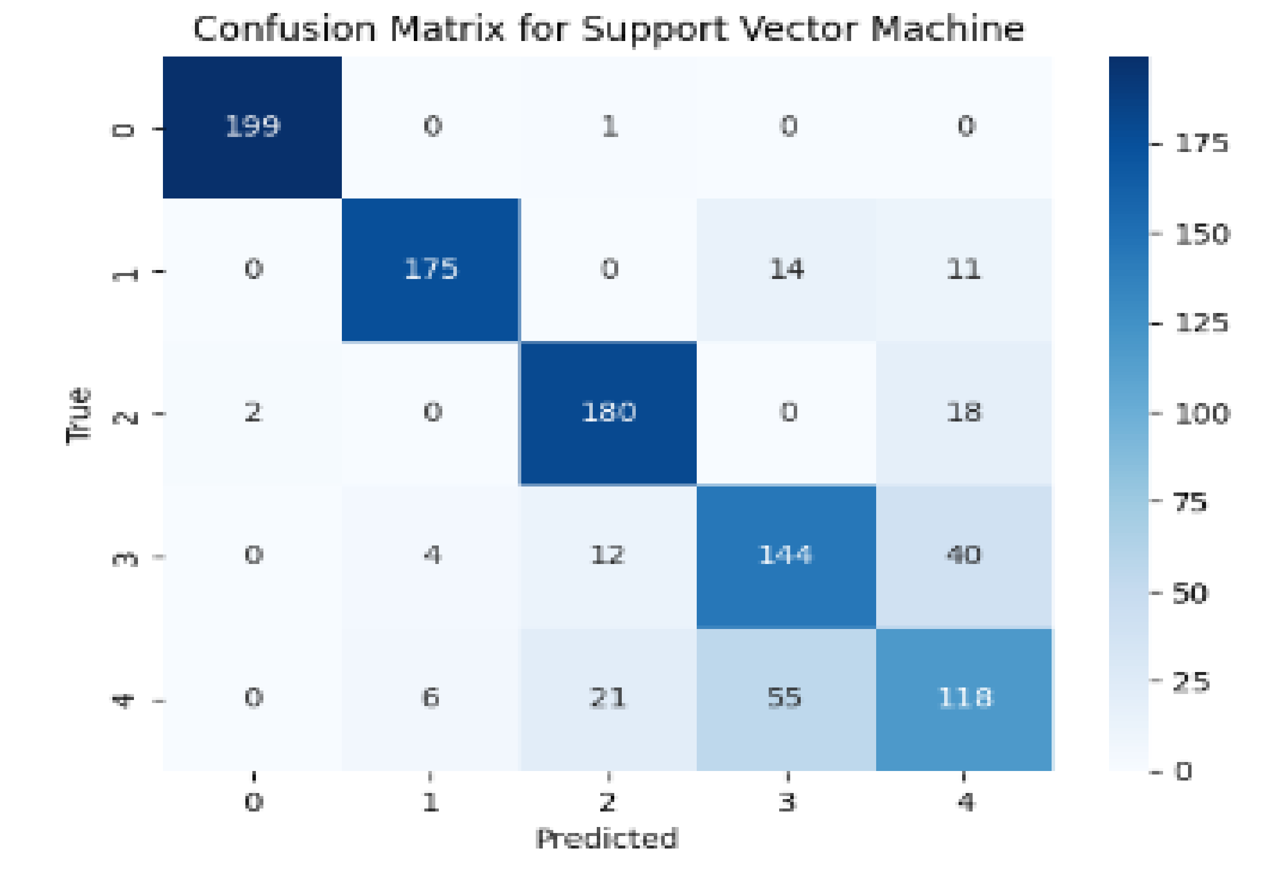
Results

Support Vector Machines (SVM)

--- Classification Report for Support Vector Machine ---

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.95	0.88	0.91	200
2	0.84	0.90	0.87	200
3	0.68	0.72	0.70	200
4	0.63	0.59	0.61	200
accuracy			0.82	1000
macro avg	0.82	0.82	0.82	1000
weighted avg	0.82	0.82	0.82	1000



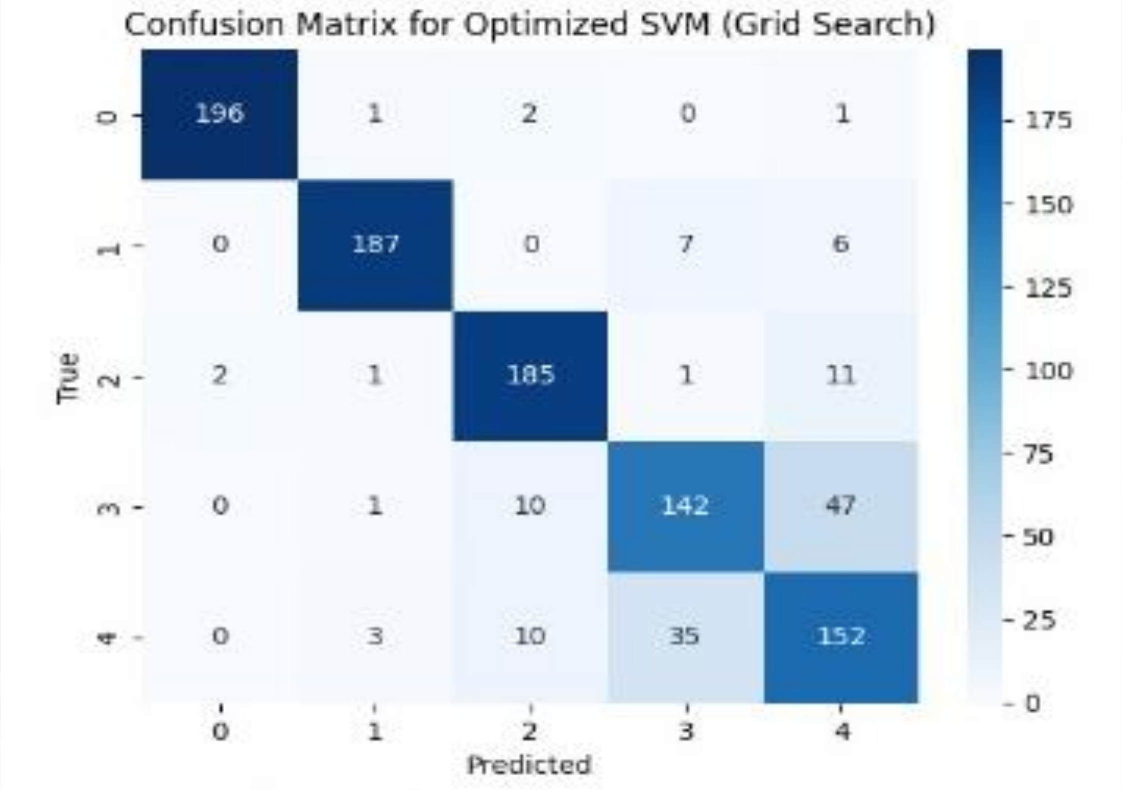
Support Vector Machines (SVM)

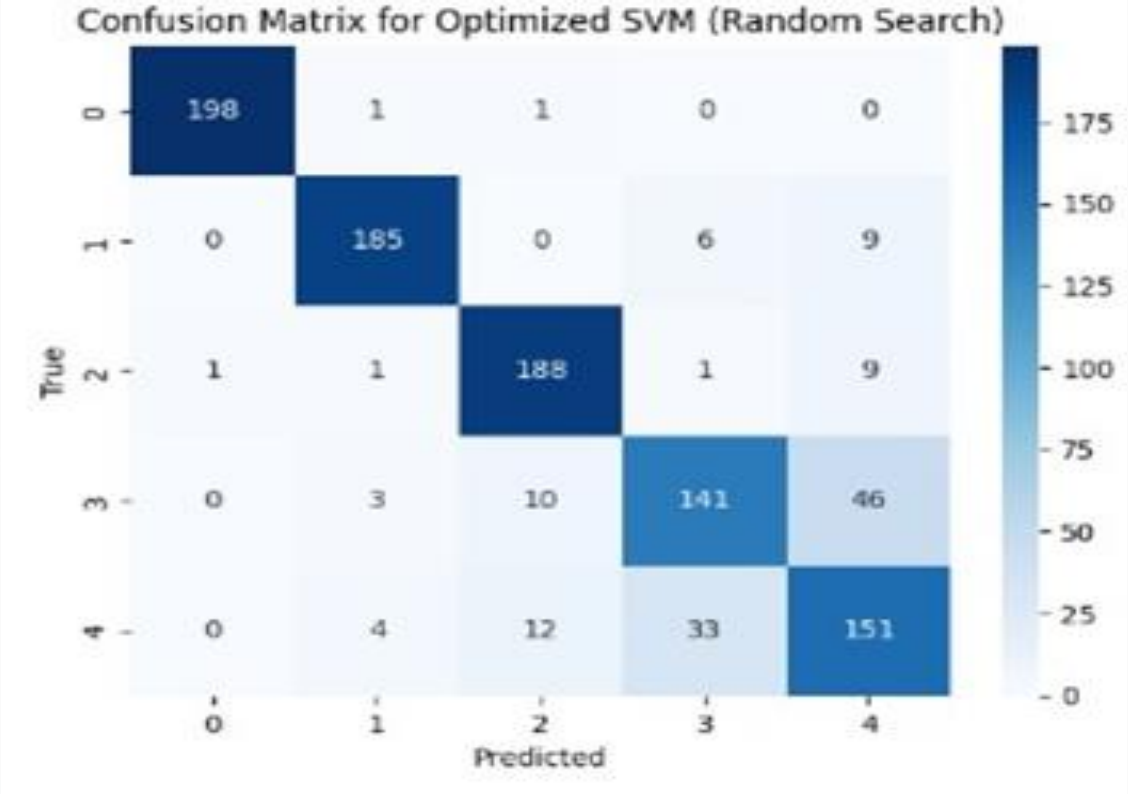
--- Classification Report for Optimized SVM (Grid Search) ---

	precision	recall	f1-score	support
0	0.99	0.98	0.98	200
1	0.97	0.94	0.95	200
2	0.89	0.93	0.91	200
3	0.77	0.71	0.74	200
4	0.70	0.76	0.73	200
accuracy			0.86	1000
macro avg	0.86	0.86	0.86	1000
weighted avg	0.86	0.86	0.86	1000

--- Classification Report for Optimized SVM (Random Search) ---

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.95	0.93	0.94	200
2	0.89	0.94	0.91	200
3	0.78	0.70	0.74	200
4	0.70	0.76	0.73	200
accuracy			0.86	1000
macro avg	0.86	0.86	0.86	1000
weighted avg	0.86	0.86	0.86	1000





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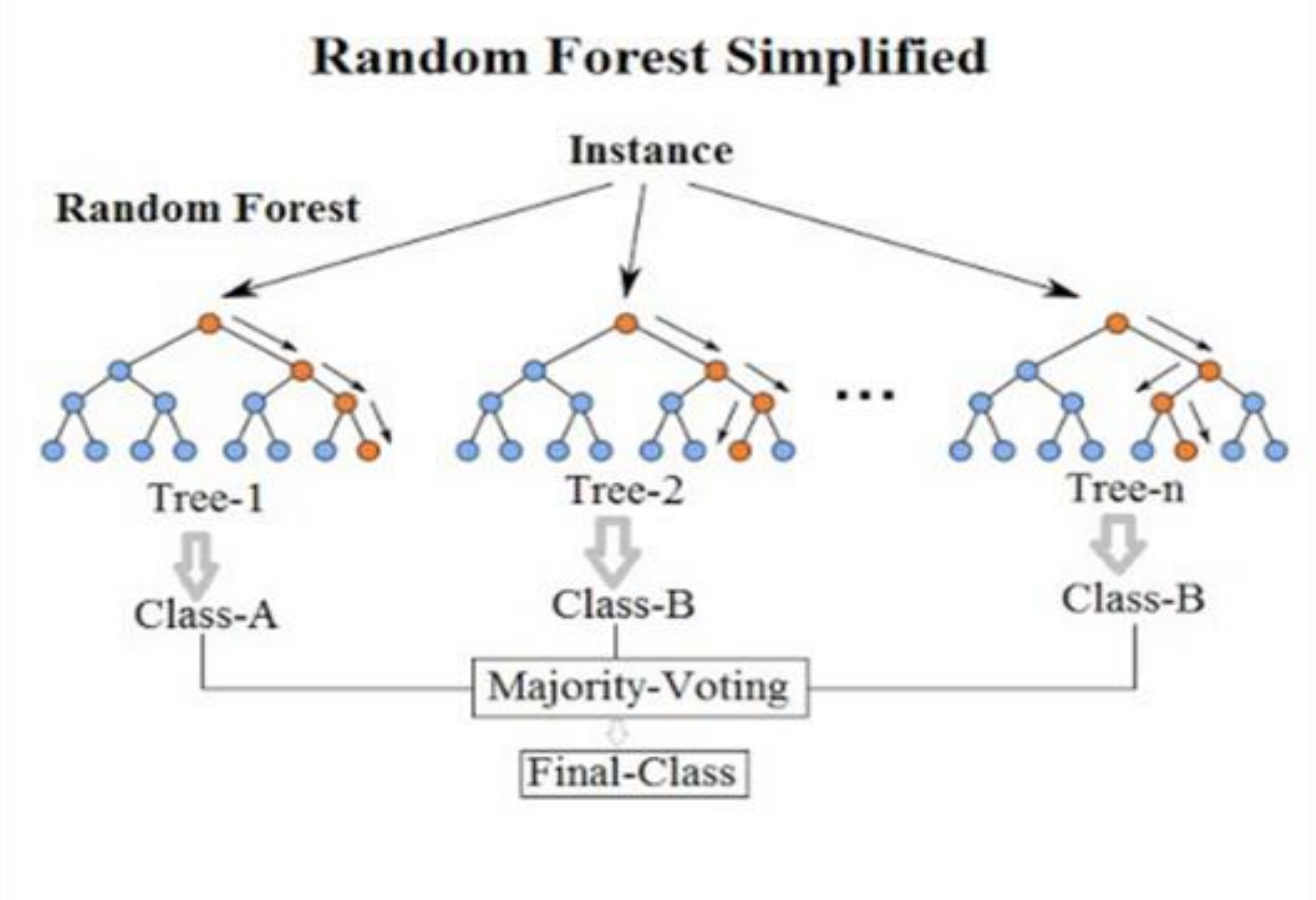
Implementation

Random Forest

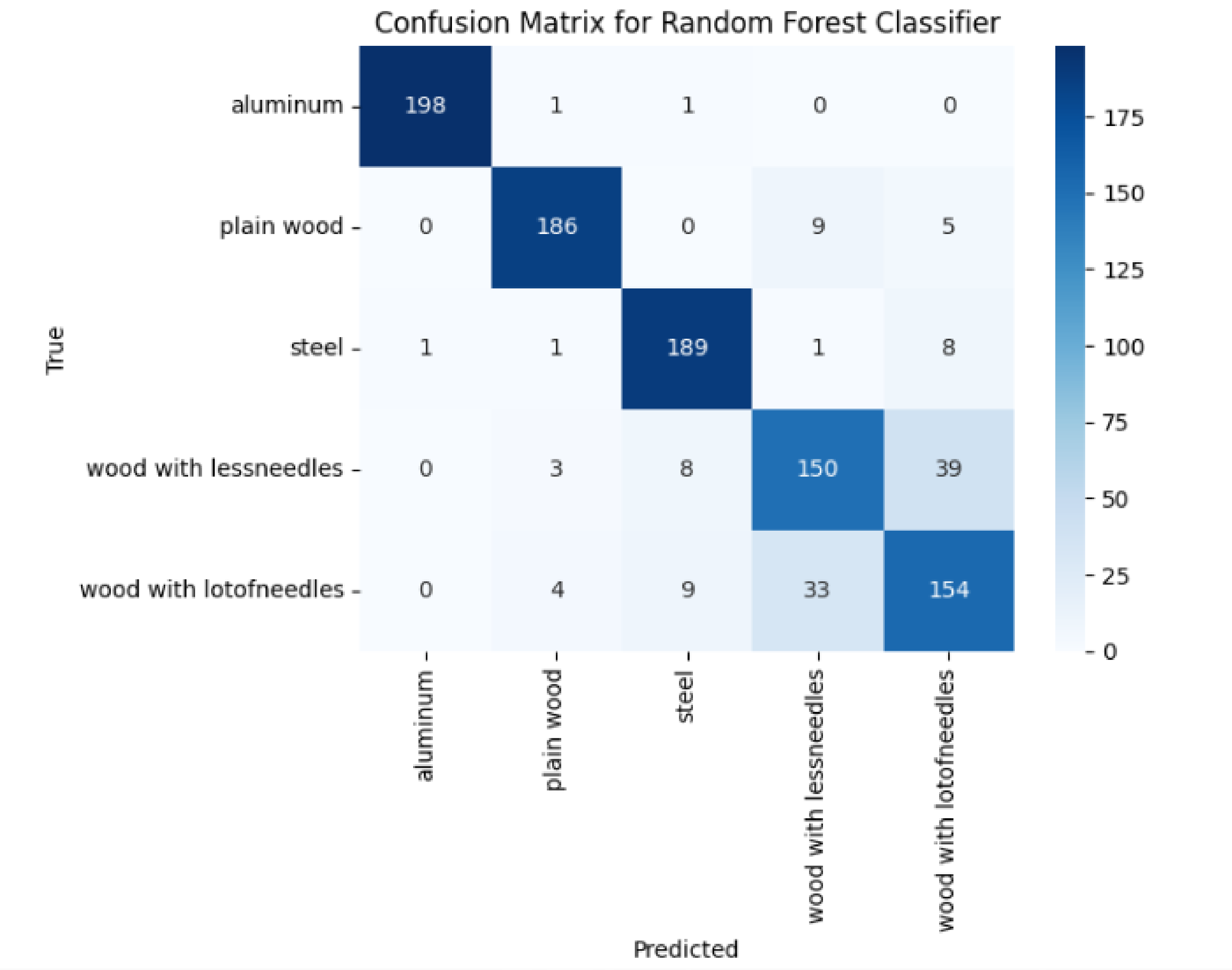


Results

Random Forest (without hyperparameter tuning)

Classification Report for Random Forest Classifier:

	precision	recall	f1-score	support
aluminum	0.99	0.99	0.99	200
plain wood	0.95	0.93	0.94	200
steel	0.91	0.94	0.93	200
wood with lessneedles	0.78	0.75	0.76	200
wood with lotofneedles	0.75	0.77	0.76	200
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000



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Results

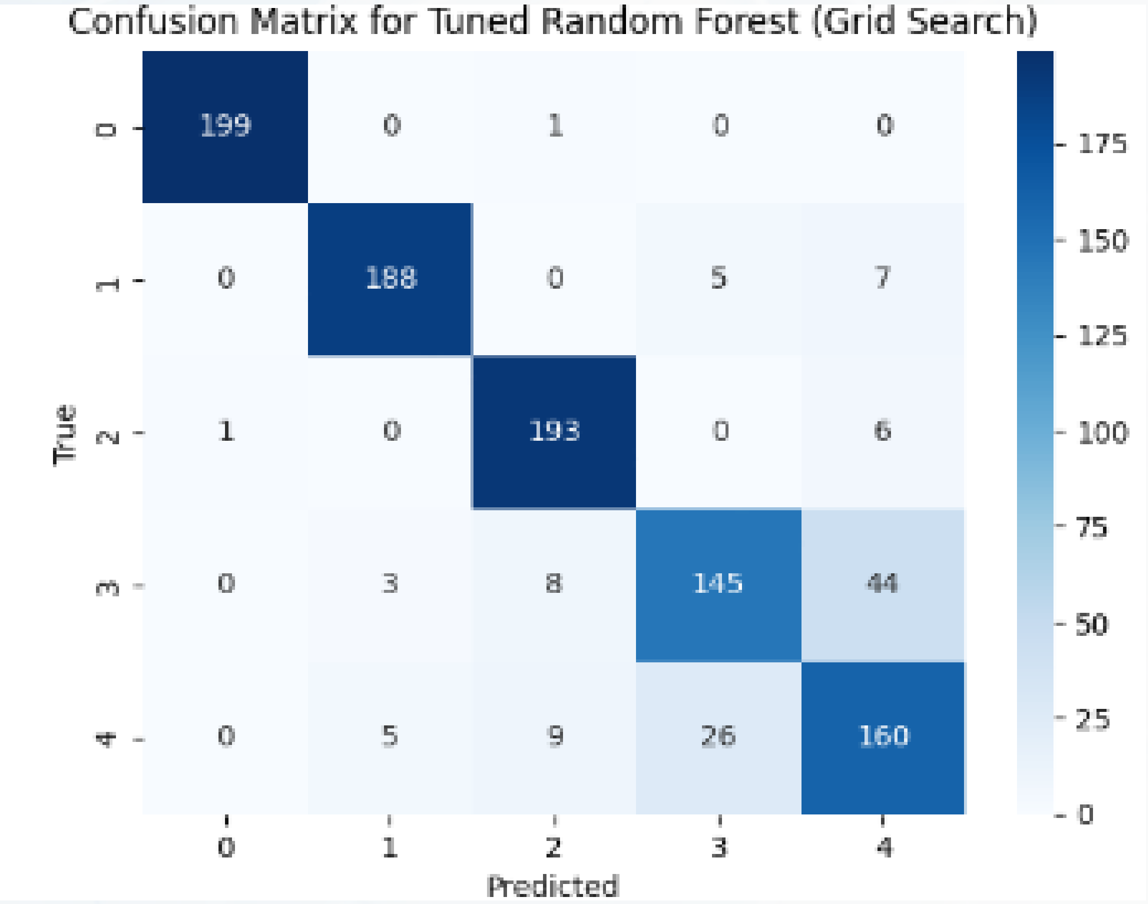
Random Forest

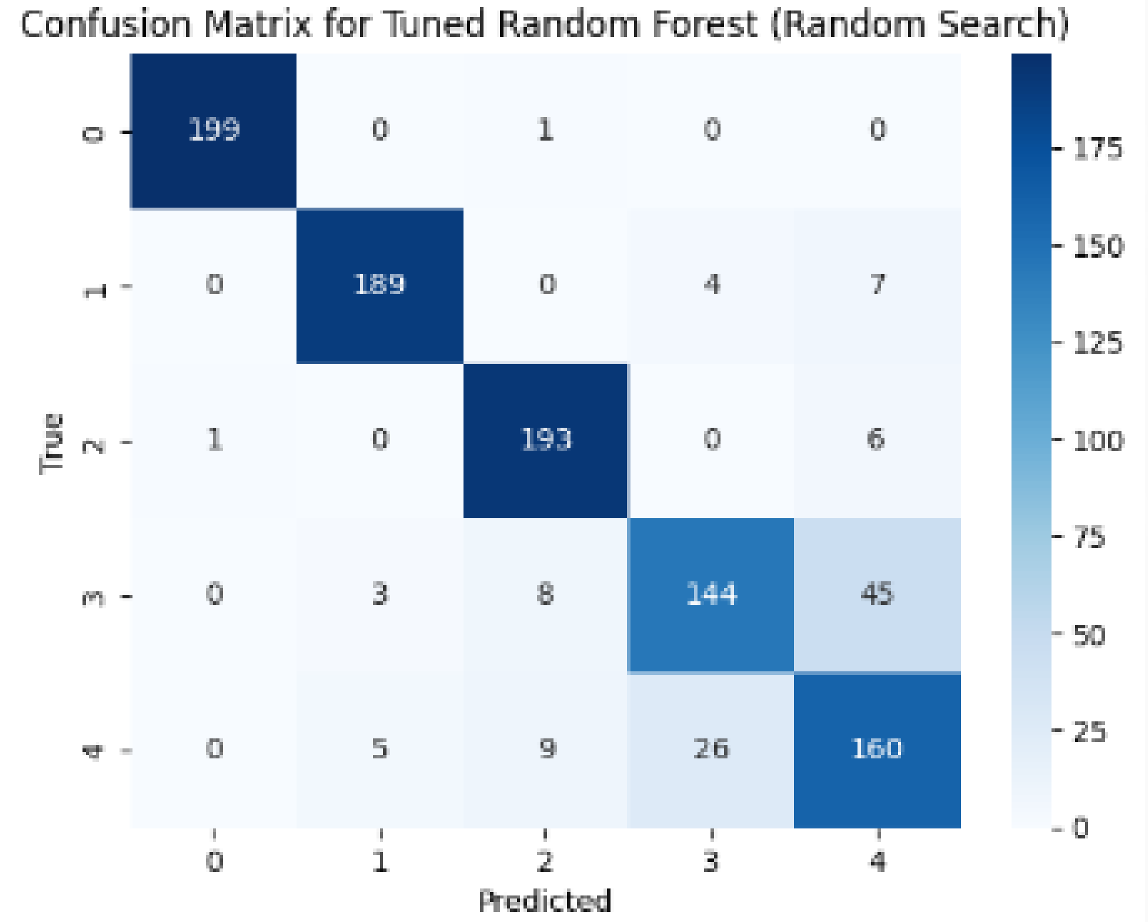
Classification Report for Tuned Random Forest (Grid Search):

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.96	0.94	0.95	200
2	0.91	0.96	0.94	200
3	0.82	0.72	0.77	200
4	0.74	0.80	0.77	200
accuracy			0.89	1000
macro avg	0.89	0.89	0.88	1000
weighted avg	0.89	0.89	0.88	1000

Classification Report for Tuned Random Forest (Random Search):

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.96	0.94	0.95	200
2	0.91	0.96	0.94	200
3	0.83	0.72	0.77	200
4	0.73	0.80	0.77	200
accuracy			0.89	1000
macro avg	0.89	0.89	0.88	1000
weighted avg	0.89	0.89	0.88	1000





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Results

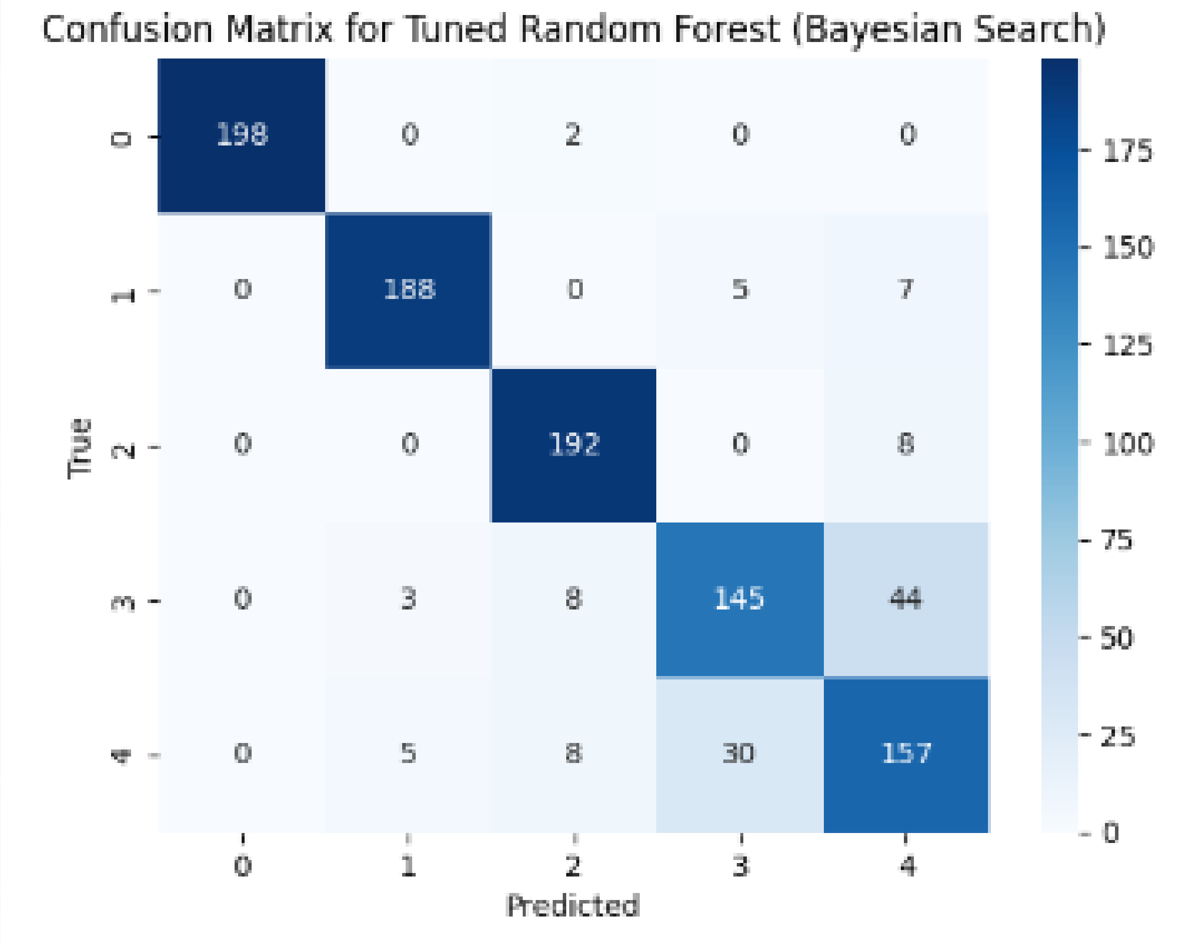
Random Forest

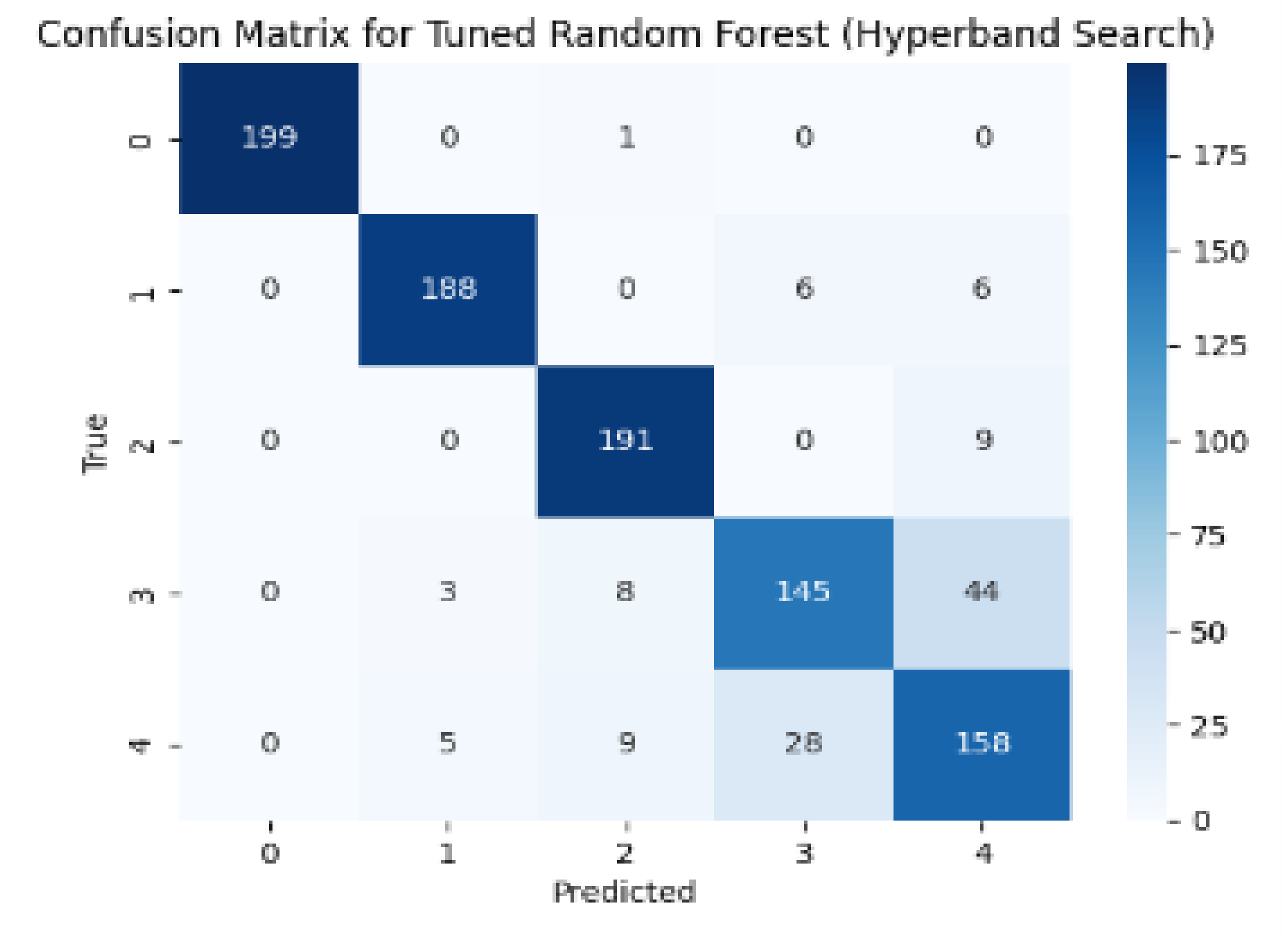
Classification Report for Tuned Random Forest (Bayesian Search):

	precision	recall	f1-score	support
0	1.00	0.99	0.99	200
1	0.96	0.94	0.95	200
2	0.91	0.96	0.94	200
3	0.81	0.72	0.76	200
4	0.73	0.79	0.75	200
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000

Classification Report for Tuned Random Forest (Hyperband Search):

	precision	recall	f1-score	support
0	1.00	0.99	1.00	200
1	0.96	0.94	0.95	200
2	0.91	0.95	0.93	200
3	0.81	0.72	0.77	200
4	0.73	0.79	0.76	200
accuracy			0.88	1000
macro avg	0.88	0.88	0.88	1000
weighted avg	0.88	0.88	0.88	1000





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Results

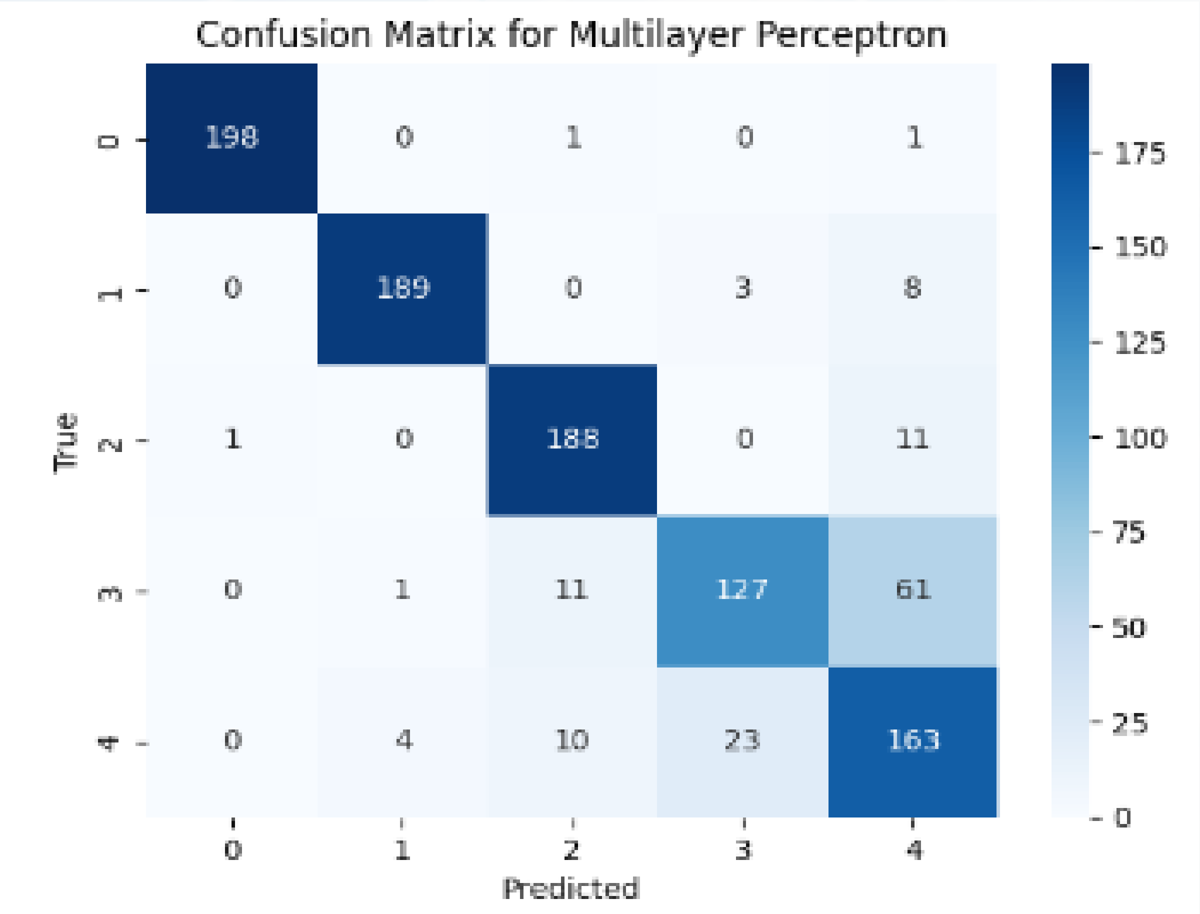
Multilayer Perceptron (MLP)

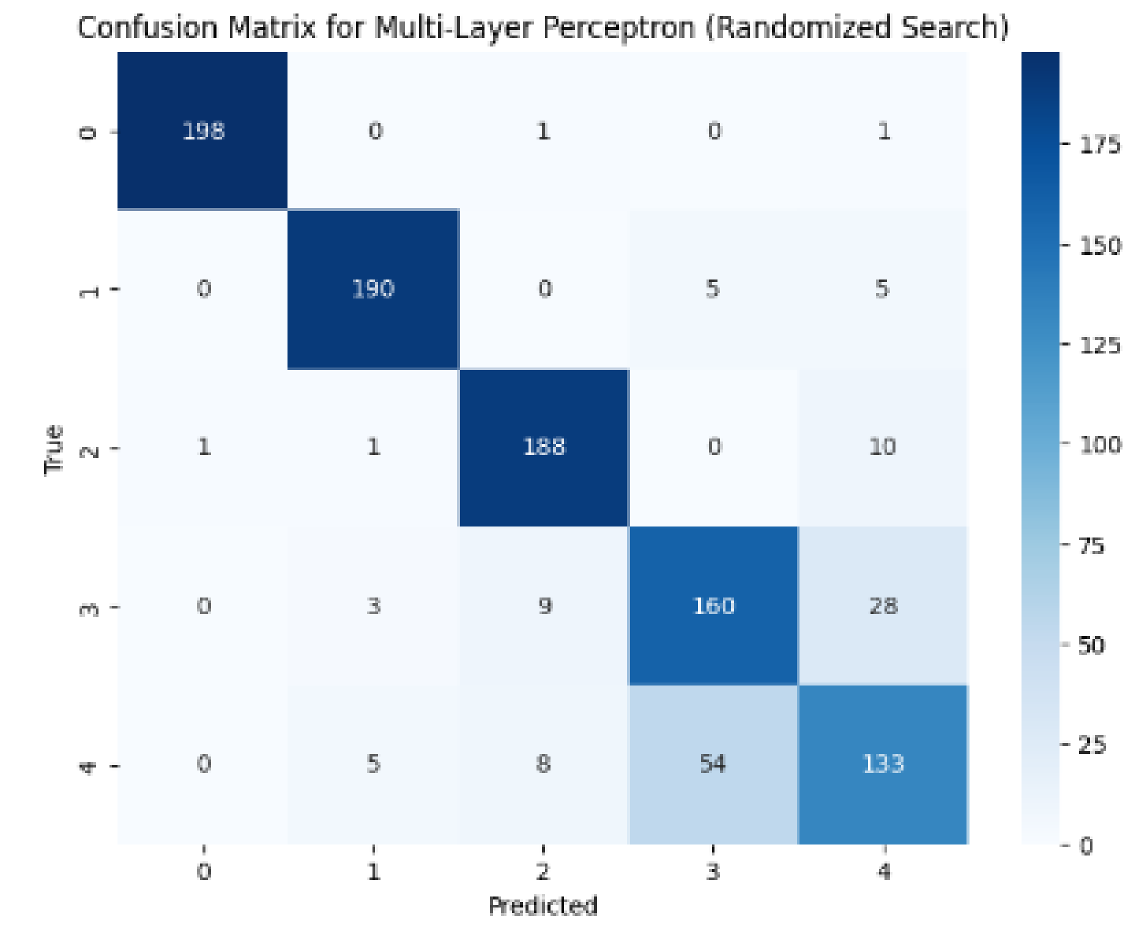
Classification Report for Multilayer Perceptron:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.97	0.94	0.96	200
2	0.90	0.94	0.92	200
3	0.83	0.64	0.72	200
4	0.67	0.81	0.73	200
accuracy			0.86	1000
macro avg	0.87	0.86	0.86	1000
weighted avg	0.87	0.86	0.86	1000

Classification Report for Multi-Layer Perceptron (Randomized Search):

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.95	0.95	0.95	200
2	0.91	0.94	0.93	200
3	0.73	0.80	0.76	200
4	0.75	0.67	0.71	200
accuracy			0.87	1000
macro avg	0.87	0.87	0.87	1000
weighted avg	0.87	0.87	0.87	1000





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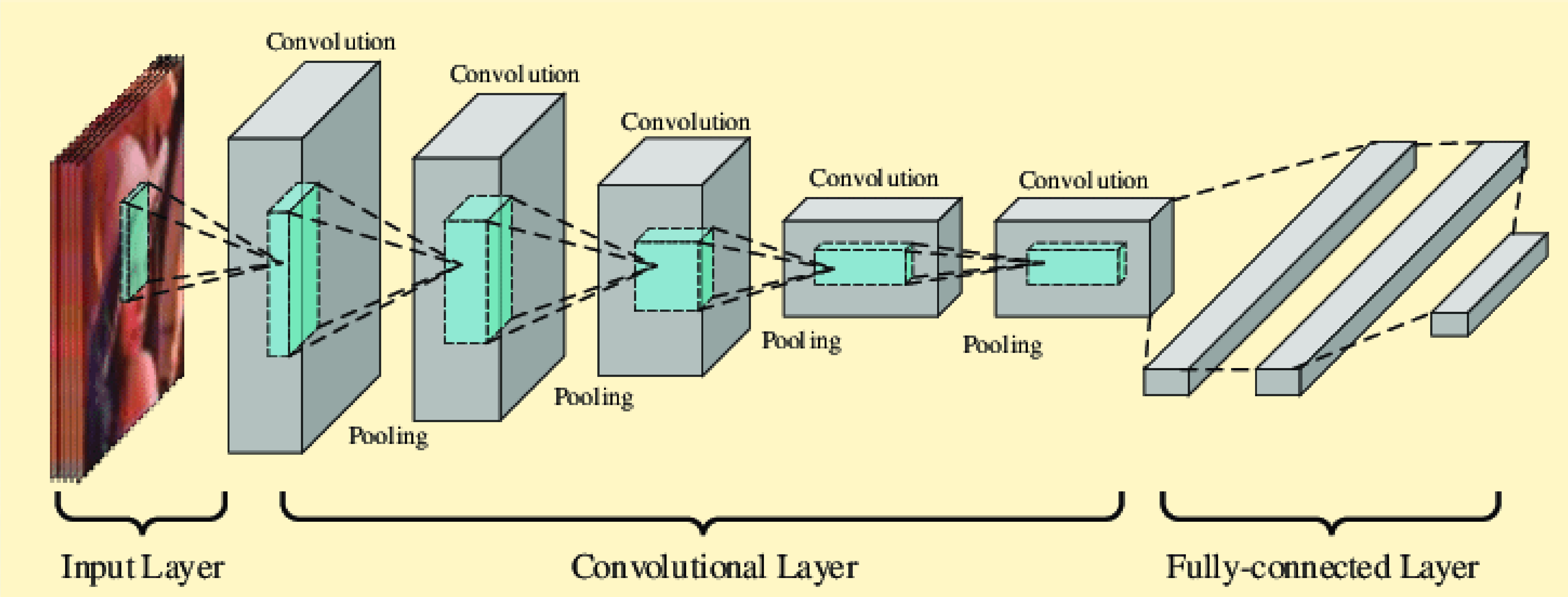
Implementation

Convolutional Neural Networks (CNN)



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Results

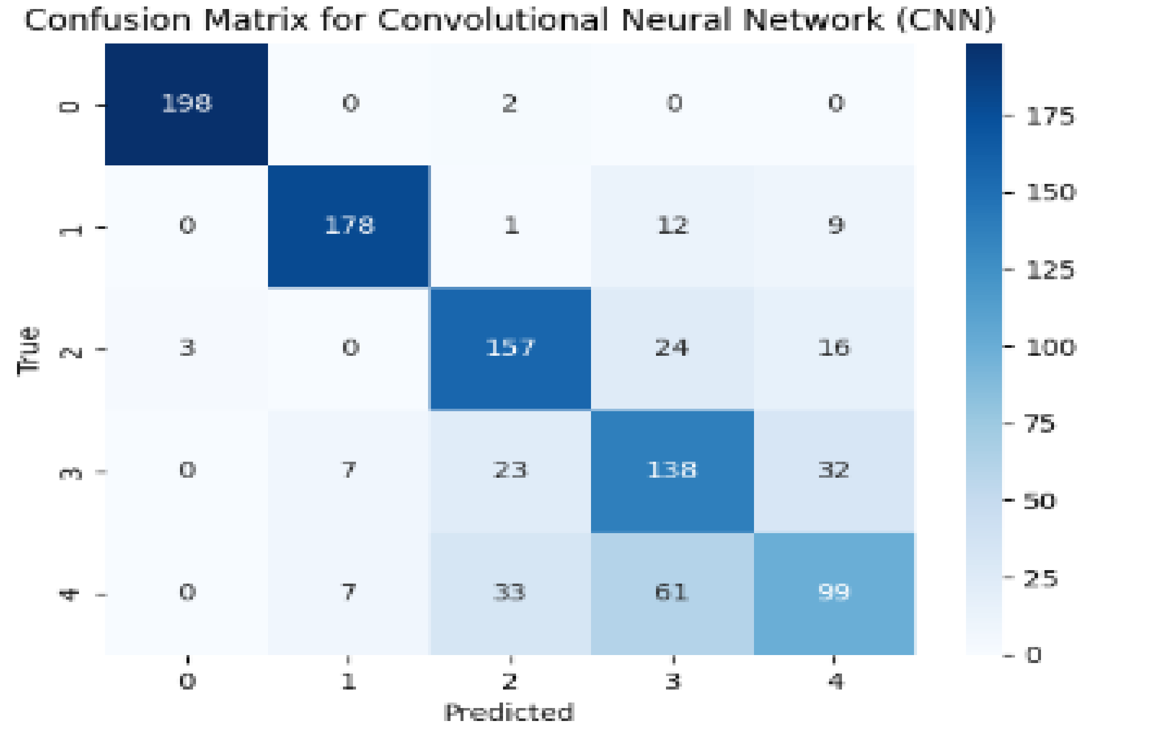
Convolutional Neural Networks (CNN)

Classification Report for Convolutional Neural Network (CNN):

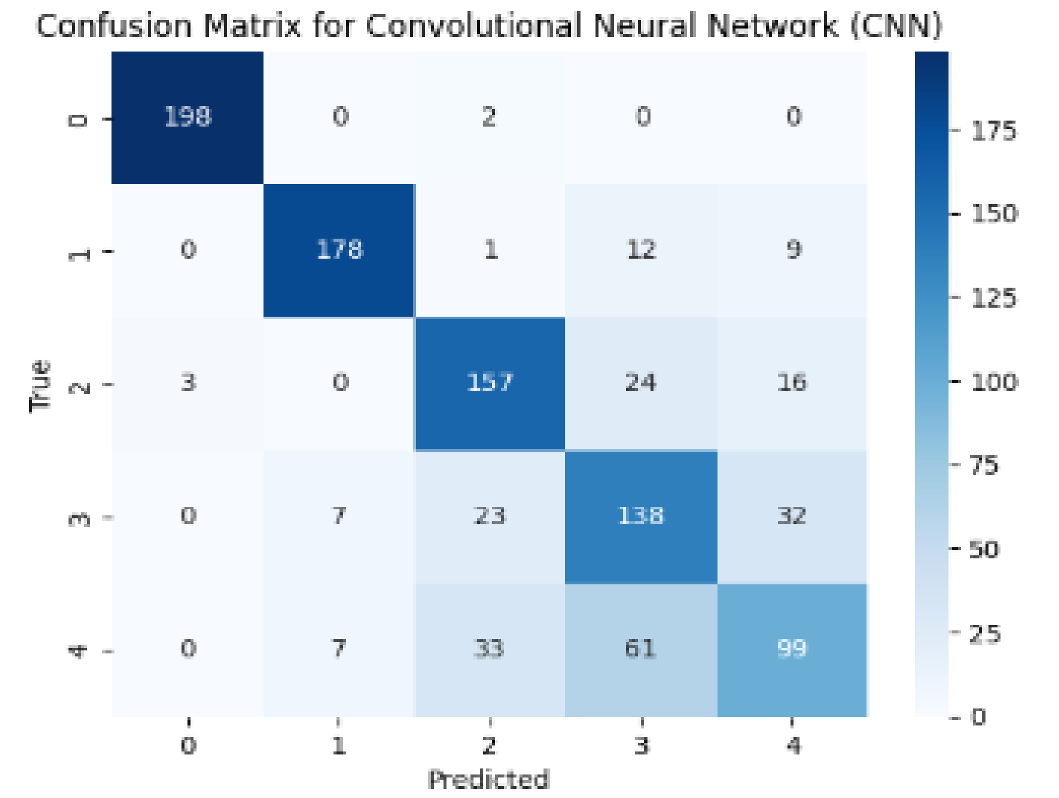
	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.93	0.89	0.91	200
2	0.73	0.79	0.75	200
3	0.59	0.69	0.63	200
4	0.63	0.49	0.56	200
accuracy			0.77	1000
macro avg	0.77	0.77	0.77	1000
weighted avg	0.77	0.77	0.77	1000

Classification Report for CNN:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.93	0.94	0.93	200
2	0.88	0.95	0.91	200
3	0.86	0.59	0.70	200
4	0.67	0.81	0.73	200
accuracy			0.86	1000
macro avg	0.87	0.86	0.86	1000
weighted avg	0.87	0.86	0.86	1000



32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.7820 - loss: 0.5644
CNN Test Accuracy: 0.7699999809265137



Results

Long Short-Term Memory (LSTM)

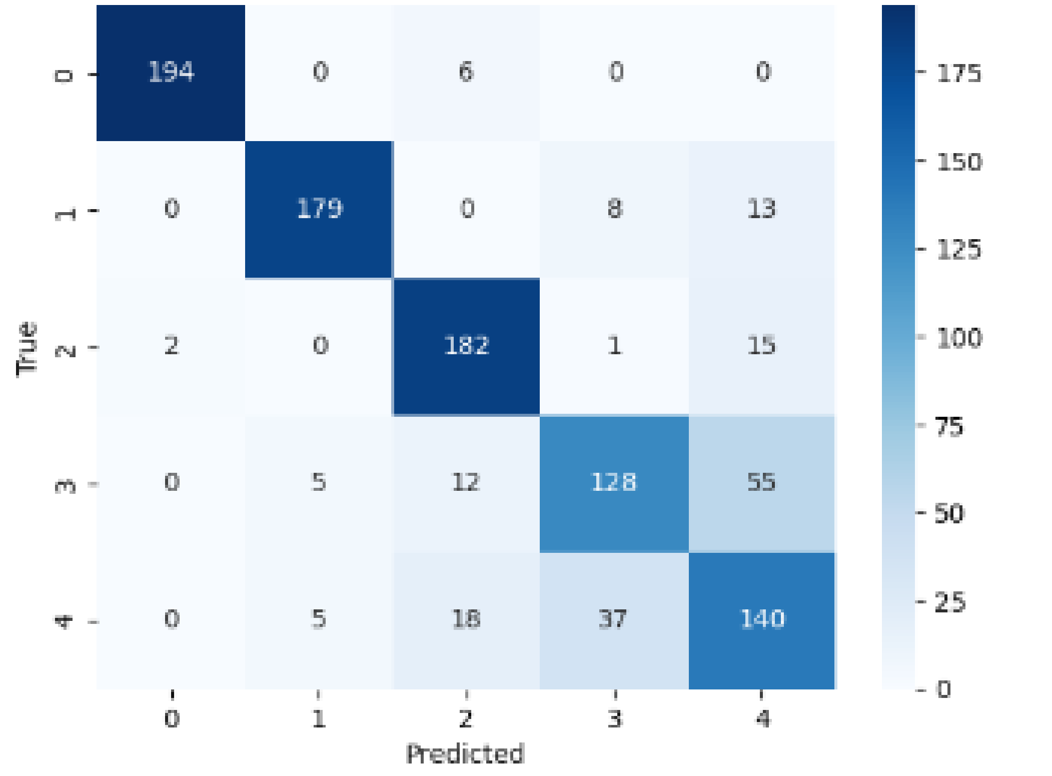
Classification Report for Long Short-Term Memory (LSTM):

	precision	recall	f1-score	support
0	0.99	0.97	0.98	200
1	0.95	0.90	0.92	200
2	0.83	0.91	0.87	200
3	0.74	0.64	0.68	200
4	0.63	0.70	0.66	200
accuracy			0.82	1000
macro avg	0.83	0.82	0.82	1000
weighted avg	0.83	0.82	0.82	1000

Classification Report for LSTM (Tuned):

	precision	recall	f1-score	support
0	0.99	0.99	0.99	200
1	0.93	0.92	0.93	200
2	0.88	0.95	0.92	200
3	0.77	0.70	0.73	200
4	0.70	0.72	0.71	200
accuracy			0.86	1000
macro avg	0.86	0.86	0.86	1000
weighted avg	0.86	0.86	0.86	1000

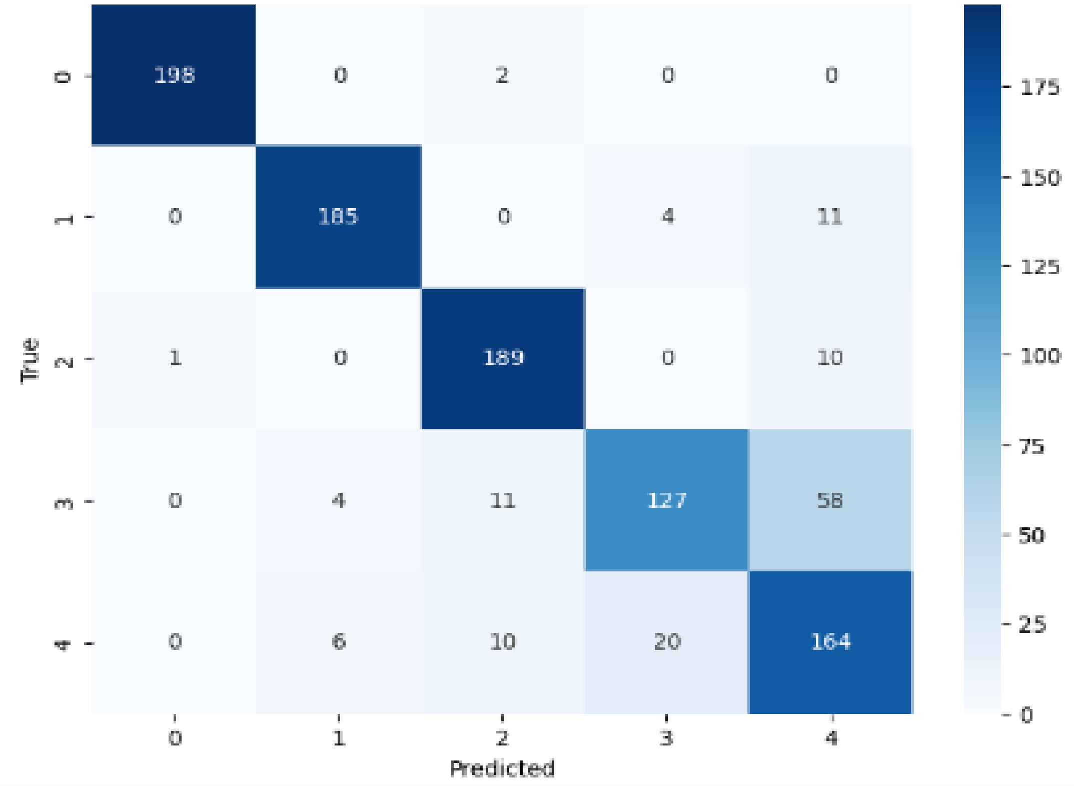
Confusion Matrix for Long Short-Term Memory (LSTM)



32/32 ━━━━━━━━━━ 0s 2ms/step - accuracy: 0.8298 - loss: 0.4288
LSTM Test Accuracy: 0.8230000138282776

Confusion Matrix for LSTM (Tuned):

Confusion Matrix for LSTM (Tuned)



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Conclusion

Analysis of Ultrasonic Signal Classification

Several machine learning models have been successfully constructed to categorize materials using ultrasonic signals that are obtained by the SRF02 sensor and the Red Pitaya STEMLAB

Impact of Hyperparameter Tuning

Models performed much better after hyperparameter adjustment, which increased their capacity to differentiate across materials.
Random Forest showed the best classification accuracy.

Key Takeaways

The integration of machine learning with feature extraction methods produced insightful results about material differentiation.
Optimizing model performance has been shown to depend heavily on tuning parameters like estimators and kernels.

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Thank You