Chapter 7

Vibration-Based Vehicle Classification Using Machine Learning Techniques

7.1 Preface

Building directly upon the vibration standardization frameworks developed in Chapter 6, specifically the RVEL and PCVE metrics that quantify and normalize the vibrational impact of different vehicle classes, this chapter advances toward real-time vehicle classification using ground vibration signatures. It operationalizes the foundational signal processing and model development methodologies detailed in Section 4.7, focusing on developing and empirical evaluation of a vibration-based classification framework.

The classification models presented here utilize tri-axial accelerometer data processed through a unified pipeline comprising FFT-based filtering, transient windowing and energy-based segmentation. A comprehensive experimental setup evaluates the accuracy and robustness of multiple machine learning configurations, spanning 126 unique feature–method combinations, to establish an optimized classifier capable of identifying vehicle types under heterogeneous traffic and road conditions.

7.2 Results

This section presents the experimental findings of the proposed work, validating its applicability using various performance metrics such as accuracy, precision, recall, F-measure, AUC and loss. Initially, the section illustrates the performance matrices, followed by a detailed description of the different experimental setups used to evaluate the proposed work.

7.2.1 Performance matrices

After executing all the methodologies described above on 126 distinct sets (as shown in Table 4.10), a comprehensive set of performance metrics was obtained for each dataset. These metrics include those for training, testing, validation and runtime. Performance metrics are essential for evaluating the efficacy of a machine-learning model. In this context, the metrics used are defined as follows:

- *Accuracy:* The ratio of correctly predicted instances to the total instances provides an overall measure of model performance.
- *Precision:* The ratio of true positive predictions to total positive predictions indicates the model's accuracy in identifying relevant instances.
- *Recall:* The ratio of true positive predictions to the actual positive instances reflects the model's ability to identify all relevant instances.
- *F1 Score:* The harmonic mean of precision and recall balances the two metrics.
- *AUC-ROC (Area Under the Receiver Operating Characteristic Curve)*: This metric evaluates the model's ability to distinguish between classes, with higher values indicating better performance.

- *Loss:* The error in the model's predictions, with lower values signifying better model performance.

This section details the results of these metrics and provides a focused analysis of the highest-performing dataset. The confusion matrix, F1 score and AUC-ROC curves are presented in detail for this top-performing set. The confusion matrix visually represents true versus predicted classifications, the F1 score encapsulates the balance between precision and recall and the AUC-ROC curve illustrates the model's diagnostic ability. These detailed evaluations underscore the model's effectiveness and reliability in accurately classifying vehicle types based on the analyzed vibration data.

7.2.1.1 Test performance

Figures 7.1, 7.2 and 7.3 showcase the performance metrics for test accuracy, test precision, test recall, test F1 score, test loss and AUC-ROC through 3-D plots. These plots map the variables, methods and performance metrics onto the X, Y and Z axes, providing a detailed visual representation of how different combinations of variables and methodologies impact the performance outcomes. The methodology behind these plots involves assessing the test data through various configurations and measuring the resulting performance metrics. Test accuracy measures the overall correctness of the model's predictions.

Upon analyzing these plots, it is apparent that *set* 85 stands out as the top performer. This set utilized the *XYZ SUM variables and the WBS method*, which includes balancing and a stacking classifier. The performance metrics for this set are particularly notable: a test loss of 0.0337%, test accuracy of 99.78%, a test AUC-ROC of *1*, a test precision of 99.78%, a test recall of 99.78% and a test F1 score of 99.78%. Another performance result of set 85 is shown in Figure 7.7; precision-recall and receiver operating characteristic (ROC) curves are shown, corroborating the top performance of set 85. These metrics demonstrate that the model accurately classifies the vehicle types and maintains high consistency and reliability across all performance indicators.

To enhance the clarity and interpretability of these results, the performance metrics for the set 85 are highlighted in the plots. Metrics are shown in red, except for the loss depicted in Blue. This color differentiation aids in quickly identifying and focusing on the most significant results. The top five values for each performance metric are prominently displayed in the respective bars, emphasizing the outstanding performance of set 85. The detailed analysis of these plots confirms the robustness and effectiveness of the proposed work. By thoroughly evaluating the various combinations of variables and methods, the model demonstrates superior performance in vehicle classification based on vibration data. The comprehensive visualization provided by the 3-D plots not only validates the proposed methodology but also highlights the critical factors contributing to the model's success.

7.2.1.2 Training and validation performance

Tables 7.1, 7.2, 7.3 show the training and validation matrices for all *126* sets. From the tables, it is observed that for training and validation processes, set 85 outperforms all other sets. These results resemble the previous findings. Further, the set 85 incurs the training loss of 0.029%, accuracy 99.76%, AUC-ROC 0.99%, precision 99.76%, recall 99.76% and F1-Score 99.76%. Similarly, the set incurs the validation loss 0.030%, accuracy 99.77%, AUC-ROC 0.99, precision 99.77%, recall 99.77% and F1-Score 99.77%. There are separate tables for RMS (Table 7.1), Max (Table 7.2) and SUM (Table 7.3) variables and the set with the maximum performance has been highlighted in the table for better understanding.

Table 7.1 Performance metrics across methods on RMS values.

Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
1	XYZ RMS	WBS	0.06	99.66	1.00	99.67	99.66	99.66	0.04	99.80	1.00	99.80	99.80	99.80
2		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	2.67	75.71	0.96	75.26	75.71	75.25
3		WBwSXGB	1.74	83.62	0.98	83.60	83.62	83.38	3.44	66.44	0.93	65.45	66.44	65.59

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Table 7.1 continued from previous page

Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
4		wBWS	1.07	88.11	0.99	81.40	88.11	83.76	4.88	64.01	0.79	57.87	64.01	58.51
5		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.73	62.59	0.77	56.63	62.59	58.99
6		wBwSXBG	1.02	92.75	1.00	92.96	92.75	92.50	4.93	62.22	0.79	56.64	62.22	58.54
7	XZ RMS	WBS	0.47	97.23	1.00	97.29	97.23	97.13	0.54	96.87	1.00	96.96	96.87	96.75
8		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.14	60.74	0.90	60.12	60.74	60.31
9		WBwSXGB	3.38	68.19	0.95	68.12	68.19	67.67	4.68	55.26	0.89	54.28	55.26	54.37
10		wBWS	3.09	75.71	0.97	73.33	75.71	69.58	5.01	63.38	0.78	52.38	63.38	57.23
11		wBwSRF	0.00	99.98	1.00	99.98	99.98	99.98	5.78	59.00	0.75	53.18	59.00	55.47
12		wBwSXBG	2.72	80.04	0.98	80.89	80.04	78.14	5.17	61.69	0.79	54.96	61.69	57.38
13	YZ RMS	WBS	0.46	97.05	1.00	97.11	97.05	96.95	0.45	97.18	1.00	97.23	97.18	97.08
14		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	3.99	61.27	0.91	60.65	61.27	60.83
15		WBwSXGB	3.13	68.78	0.95	68.57	68.78	68.32	4.51	55.97	0.90	55.11	55.97	55.22
16		wBWS	2.89	76.27	0.97	67.97	76.27	70.09	4.92	64.01	0.78	53.15	64.01	57.97
17		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	5.25	61.32	0.75	55.34	61.32	57.50
18		wBwSXBG	2.81	80.21	0.98	81.24	80.21	78.46	5.07	62.74	0.79	55.82	62.74	58.21
19	XY RMS	WBS	0.64	95.75	1.00	95.95	95.75	95.49	0.66	95.83	1.00	95.99	95.83	95.54
20		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.76	57.85	0.89	57.04	57.85	57.34
21		WBwSXGB	3.85	64.97	0.94	64.59	64.97	64.53	5.44	52.02	0.87	51.02	52.02	51.36
22		wBWS	4.91	71.54	0.96	65.28	71.54	65.26	7.36	58.84	0.74	47.44	58.84	50.79
23		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	7.35	54.30	0.69	48.74	54.30	50.78
24		wBwSXBG	4.09	76.31	0.97	77.81	76.31	74.07	6.92	56.62	0.74	49.12	56.62	51.59
25	X RMS	WBS	4.42	63.64	0.90	64.25	63.64	62.96	4.31	64.04	0.90	65.06	64.04	63.49
26		WBwSRF	0.02	99.76	1.00	99.76	99.76	99.76	7.34	31.56	0.73	31.36	31.56	31.45
27		WBwSXGB	6.51	38.72	0.81	37.87	38.72	37.60	6.64	37.51	0.80	36.28	37.51	36.35
28		wBWS	7.26	60.19	0.77	48.72	60.19	52.68	7.49	58.42	0.73	45.66	58.42	50.27
29		wBwSRF	0.01	99.86	1.00	99.86	99.86	99.86	8.62	46.75	0.62	45.45	46.75	46.04
30		wBwSXBG	6.76	60.99	0.86	50.51	60.99	54.96	6.98	58.31	0.73	46.86	58.31	51.62
31	Y RMS	WBS	4.32	65.60	0.91	65.62	65.60	65.17	4.21	66.71	0.91	66.76	66.71	66.28
32		WBwSRF	0.03	99.73	1.00	99.73	99.73	99.73	7.96	29.28	0.71	29.22	29.28	29.23
33		WBwSXGB	7.16	36.61	0.80	35.54	36.61	35.57	7.43	34.56	0.78	33.25	34.56	33.42
34		wBWS	8.37	58.26	0.81	46.60	58.26	48.88	8.96	56.83	0.70	43.98	56.83	47.17
35		wBwSRF	0.02	99.89	1.00	99.89	99.89	99.89	10.95	40.90	0.61	41.08	40.90	40.95
36		wBwSXBG	8.09	58.49	0.84	49.96	58.49	52.24	8.33	55.83	0.70	46.11	55.83	48.72
37	Z RMS	WBS	4.06	63.92	0.90	64.55	63.92	63.96	4.11	64.11	0.91	65.06	64.11	64.22
38		WBwSRF	0.02	99.79	1.00	99.79	99.79	99.79	6.65	31.45	0.73	31.54	31.45	31.48
39		WBwSXGB	5.76	39.51	0.82	38.90	39.51	38.95	5.83	38.27	0.81	37.72	38.27	37.73

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Table 7.1 continued from previous page

Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
40		wBWS	4.39	67.32	0.86	56.61	67.32	61.39	4.64	65.12	0.76	54.01	65.12	58.95
41		wBwSRF	0.01	99.95	1.00	99.95	99.95	99.95	6.55	53.46	0.65	51.53	53.46	52.43
42		wBwSXBG	4.37	67.65	0.88	57.06	67.65	61.84	4.63	65.01	0.76	54.10	65.01	58.98

Table 7.2 Performance metrics across methods on Max values.

Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
43	XYZ Max	WBS	0.06	99.42	1.00	99.43	99.42	99.42	0.04	99.47	1.00	99.48	99.47	99.47
44		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	3.48	72.02	0.94	71.04	72.02	71.27
45		WBwSXGB	1.99	82.92	0.98	82.77	82.92	82.66	4.28	62.91	0.91	61.69	62.91	62.02
46		wBWS	2.23	83.24	0.99	77.26	83.24	77.18	7.25	58.15	0.73	48.48	58.15	51.72
47		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	7.13	55.78	0.72	49.46	55.78	51.56
48		wBwSXBG	1.43	91.87	1.00	92.20	91.87	91.68	7.05	56.62	0.73	50.32	56.62	52.23
49	XZ Max	WBS	0.50	96.74	1.00	96.84	96.74	96.57	0.40	96.98	1.00	97.07	96.98	96.83
50		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.72	57.06	0.89	56.42	57.06	56.65
51		WBwSXGB	3.68	66.08	0.94	65.74	66.08	65.67	5.08	51.22	0.87	50.18	51.22	50.54
52		wBWS	3.96	72.21	0.96	62.38	72.21	65.45	7.59	57.31	0.72	45.43	57.31	49.78
53		wBwSRF	0.00	99.98	1.00	99.98	99.98	99.98	7.73	53.40	0.69	47.43	53.40	49.67
54		wBwSXBG	3.61	78.72	0.98	80.20	78.72	76.97	7.23	54.93	0.72	48.24	54.93	50.39
55	YZ Max	WBS	0.54	96.66	1.00	96.78	96.66	96.49	0.44	96.79	1.00	96.93	96.79	96.64
56		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.66	57.73	0.89	57.12	57.73	57.35
57		WBwSXGB	3.62	66.42	0.94	66.15	66.42	66.02	5.09	51.90	0.87	51.25	51.90	51.33
58		wBWS	3.26	75.95	0.95	64.61	75.95	69.48	7.17	58.26	0.72	46.99	58.26	51.57
59		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	7.26	54.72	0.70	48.98	54.72	51.02
60		wBwSXBG	3.69	78.29	0.98	79.82	78.29	76.36	7.01	56.15	0.73	48.09	56.15	51.25
61	XY Max	WBS	0.57	97.18	1.00	97.29	97.18	97.06	0.57	97.30	1.00	97.38	97.30	97.18
62		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	5.50	55.96	0.87	55.03	55.96	55.37
63		WBwSXGB	4.03	65.10	0.93	64.52	65.10	64.44	5.87	49.68	0.85	48.49	49.68	48.84
64		wBWS	7.04	62.53	0.92	60.14	62.53	52.39	11.26	52.77	0.69	41.11	52.77	42.50
65		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	10.95	46.17	0.64	40.20	46.17	42.55
66		wBwSXBG	5.11	74.88	0.97	76.64	74.88	73.04	10.51	48.81	0.68	40.95	48.81	43.95
67	X Max	WBS	3.99	69.61	0.91	69.54	69.61	68.57	4.12	68.65	0.91	68.78	68.65	67.74
68		WBwSRF	0.07	99.58	1.00	99.58	99.58	99.58	7.95	28.37	0.69	28.39	28.37	28.37
69		WBwSXGB	6.63	34.17	0.77	33.61	34.17	33.21	6.87	30.81	0.74	30.09	30.81	29.82
70		wBWS	14.76	46.37	0.76	28.12	46.37	34.30	14.98	45.49	0.65	28.23	45.49	33.70
71		wBwSRF	0.19	99.00	1.00	99.00	99.00	99.00	13.57	34.35	0.57	34.24	34.35	34.28

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Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
72		wBwSXBG	11.69	51.03	0.81	41.22	51.03	44.52	13.15	45.33	0.66	34.67	45.33	38.38
73	Y Max	WBS	4.92	64.68	0.89	64.37	64.68	64.04	4.93	64.82	0.89	64.42	64.82	64.19
74		WBwSRF	0.07	99.54	1.00	99.54	99.54	99.54	8.31	27.50	0.70	27.47	27.50	27.47
75		WBwSXGB	7.18	34.94	0.78	34.03	34.94	33.89	7.47	33.51	0.76	32.33	33.51	32.40
76		wBWS	10.05	56.34	0.77	53.80	56.34	47.15	10.82	53.03	0.68	40.30	53.03	43.43
77		wBwSRF	0.21	98.82	1.00	98.82	98.82	98.82	11.20	39.68	0.58	39.21	39.68	39.40
78		wBwSXBG	9.40	55.87	0.83	45.80	55.87	49.14	10.15	52.40	0.67	40.66	52.40	44.97
79	Z Max	WBS	4.20	61.58	0.90	61.81	61.58	61.01	4.03	61.09	0.89	61.27	61.09	60.52
80		WBwSRF	0.06	99.56	1.00	99.56	99.56	99.56	7.00	29.58	0.70	29.66	29.58	29.61
81		WBwSXGB	6.05	36.89	0.80	36.13	36.89	35.95	6.35	33.10	0.77	32.48	33.10	32.31
82		wBWS	6.59	59.16	0.72	47.34	59.16	51.59	7.30	57.94	0.71	46.02	57.94	50.60
83		wBwSRF	0.23	98.52	1.00	98.53	98.52	98.52	8.34	47.70	0.63	46.60	47.70	47.10
84		wBwSXBG	6.16	62.13	0.85	51.67	62.13	56.16	6.97	57.36	0.71	46.73	57.36	51.28

Table 7.3 Performance metrics across methods on SUM values.

Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
85	**XYZ SUM**	**WBS**	**0.03**	**99.76**	**1.00**	**99.76**	**99.76**	**99.76**	**0.0**	**99.77**	**1.00**	**99.77**	**99.77**	**99.77**
86		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	2.75	75.18	0.96	74.56	75.18	74.63
87		WBwSXGB	1.72	83.87	0.98	83.88	83.87	83.69	3.58	67.28	0.93	66.38	67.28	66.42
88		wBWS	1.15	87.74	0.99	81.19	87.74	83.00	4.88	64.49	0.79	60.68	64.49	58.80
89		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.85	63.91	0.77	58.44	63.91	60.23
90		wBwSXBG	1.08	92.08	1.00	92.36	92.08	91.81	4.78	64.06	0.80	58.86	64.06	60.42
91	XZ SUM	WBS	0.41	97.35	1.00	97.42	97.35	97.26	0.44	97.33	1.00	97.41	97.33	97.23
92		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.41	59.46	0.90	58.82	59.46	59.01
93		WBwSXGB	3.33	68.06	0.95	68.00	68.06	67.49	4.82	54.38	0.89	53.59	54.38	53.62
94		wBWS	3.03	76.15	0.97	73.65	76.15	70.17	5.10	63.48	0.77	52.52	63.48	57.37
95		wBwSRF	0.00	99.96	1.00	99.96	99.96	99.96	5.63	59.58	0.75	53.15	59.58	55.81
96		wBwSXBG	2.77	79.23	0.98	80.35	79.23	77.25	5.12	62.48	0.79	55.99	62.48	58.02
97	YZ SUM	WBS	0.49	96.89	1.00	96.96	96.89	96.77	0.52	96.98	1.00	97.03	96.98	96.87
98		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.02	61.30	0.91	60.82	61.30	60.99
99		WBwSXGB	3.08	68.98	0.95	68.82	68.98	68.59	4.45	55.96	0.89	55.21	55.96	55.37
100		wBWS	3.00	76.38	0.98	68.07	76.38	70.29	4.95	64.43	0.78	53.33	64.43	58.23
101		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	5.17	61.79	0.75	55.97	61.79	58.01
102		wBwSXBG	2.81	79.68	0.98	80.75	79.68	77.87	5.05	62.96	0.80	57.00	62.96	58.56
103	XY SUM	WBS	0.56	96.20	1.00	96.35	96.20	95.96	0.57	96.12	1.00	96.27	96.12	95.87

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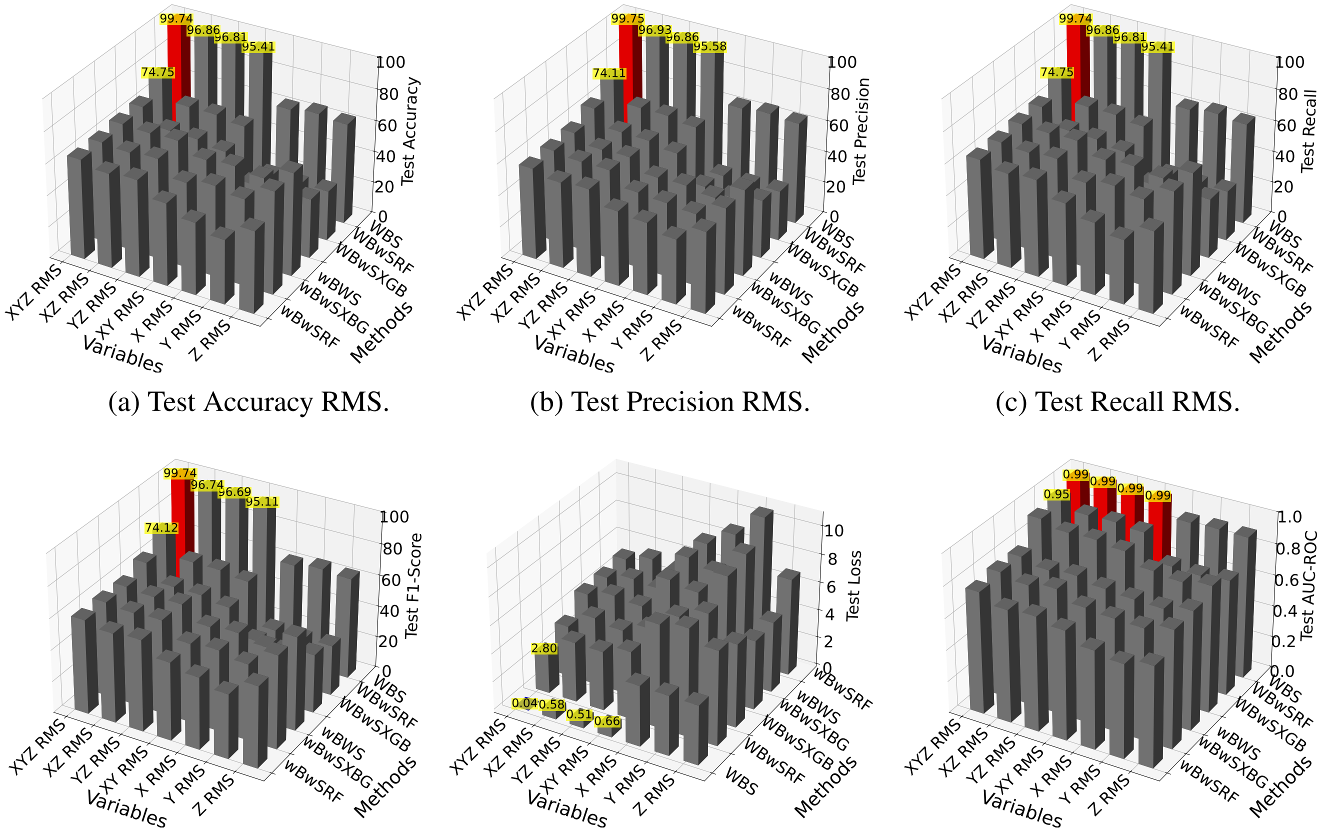
Set No.	Set Vars	Methods	TrL	TrA	TrAUC	TrP	TrR	TrF1	VL	VAcc	VAUC	VP	VR	VF1
104		WBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	4.68	58.10	0.89	57.27	58.10	57.54
105		WBwSXGB	3.67	65.69	0.94	65.35	65.69	65.29	5.10	52.62	0.87	51.83	52.62	51.93
106		wBWS	4.66	73.97	0.96	67.37	73.97	68.33	7.19	59.00	0.74	48.24	59.00	51.59
107		wBwSRF	0.00	100.00	1.00	100.00	100.00	100.00	7.31	54.14	0.69	48.97	54.14	50.82
108		wBwSXBG	4.04	75.30	0.97	76.53	75.30	73.02	6.77	57.15	0.74	50.61	57.15	52.30
109	X SUM	WBS	4.37	64.04	0.90	65.18	64.04	63.66	4.39	64.49	0.90	65.43	64.49	63.96
110		WBwSRF	0.03	99.73	1.00	99.73	99.73	99.73	7.26	31.51	0.73	31.30	31.51	31.39
111		WBwSXGB	6.74	38.03	0.81	37.51	38.03	37.02	6.86	36.64	0.79	35.80	36.64	35.44
112		wBWS	6.93	60.97	0.75	50.05	60.97	54.25	7.29	59.31	0.73	47.31	59.31	51.81
113		wBwSRF	0.01	99.86	1.00	99.86	99.86	99.86	8.62	46.60	0.61	45.22	46.60	45.85
114		wBwSXBG	6.73	61.27	0.86	50.82	61.27	55.25	7.15	57.78	0.73	46.37	57.78	51.12
115	Y SUM	WBS	4.02	65.84	0.91	66.09	65.84	65.49	4.08	65.99	0.91	66.62	65.99	65.79
116		WBwSRF	0.02	99.78	1.00	99.78	99.78	99.78	7.99	29.81	0.71	29.83	29.81	29.81
117		WBwSXGB	6.97	36.84	0.80	35.92	36.84	36.06	7.03	34.98	0.78	34.02	34.98	34.21
118		wBWS	8.11	59.31	0.82	49.09	59.31	51.16	8.63	57.15	0.70	44.29	57.15	48.16
119		wBwSRF	0.02	99.89	1.00	99.89	99.89	99.89	10.94	41.53	0.61	41.60	41.53	41.52
120		wBwSXBG	7.99	58.54	0.84	48.10	58.54	52.21	8.06	56.73	0.71	45.04	56.73	49.64
121	Z SUM	WBS	4.35	62.15	0.90	62.99	62.15	62.22	4.41	62.93	0.90	63.74	62.93	63.00
122		WBwSRF	0.02	99.80	1.00	99.80	99.80	99.80	6.68	32.50	0.74	32.52	32.50	32.48
123		WBwSXGB	5.88	39.31	0.82	38.82	39.31	38.69	6.05	38.77	0.81	38.29	38.77	38.28
124		wBWS	4.40	67.34	0.85	56.76	67.34	61.53	4.63	65.22	0.76	54.22	65.22	59.12
125		wBwSRF	0.01	99.95	1.00	99.95	99.95	99.95	6.57	53.83	0.65	51.83	53.83	52.76
126		wBwSXBG	4.34	68.00	0.88	57.44	68.00	62.23	4.63	64.85	0.76	53.93	64.85	58.82

7.2.1.3 Confusion matrix of set 85

Figure 7.4 shows the confusion matrix of set 85 for the training, testing and validation. From the figure, the training, testing and validation performance for all eight vehicle classes was observed. The figure shows that the set 85 model has very few biases towards the 1^{st} class, *i.e.*, trucks with the highest data points and the other classes with zero biases. Overall, the model is performing well in all the confusion matrices.



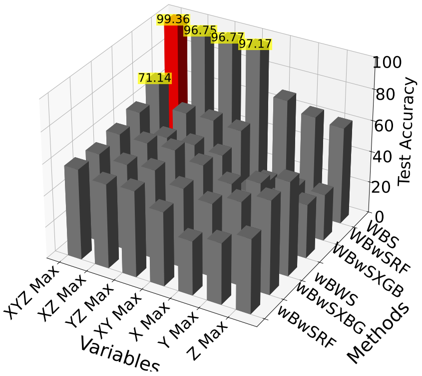
(a) Test Accuracy RMS. (b) Test Precision RMS. (c) Test Recall RMS.

(d) Test F1 Score RMS. (e) Test Loss RMS. (f) Test AUC-ROC RMS.

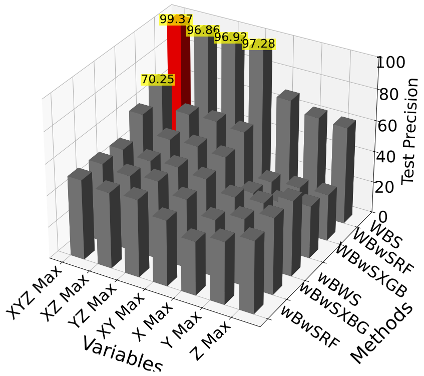
Fig. 7.1 Illustration of the performance metrics for RMS case

7.2.2 Statistical Significance Analysis of Set 85th Test Accuracy

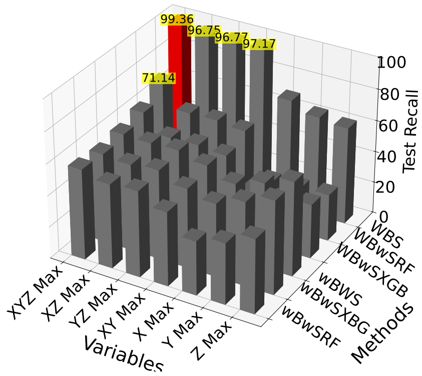
The performance of the proposed vehicle classification model was evaluated over 50 independent iterations by repeatedly partitioning the balanced dataset into training, validation and test sets. In each iteration, the best-performing configuration that uses the XYZ SUM variable combination (i.e., the summation of all squared values for the X, Y and Z directions of the vibration signal) with the WBS method (With Data Balancing With Stacking Classifier) was applied to train and test the model. The model was evaluated over 50 independent iterations by partitioning the balanced dataset into training, validation and test sets with separate random numbers. Key performance metrics were computed, including mean test accuracy and 95% confidence interval. The XYZ SUM variable combination



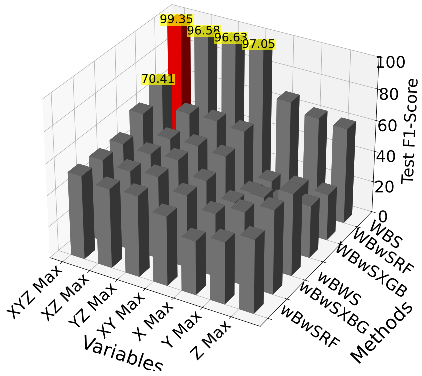
(a) Test Accuracy Max.



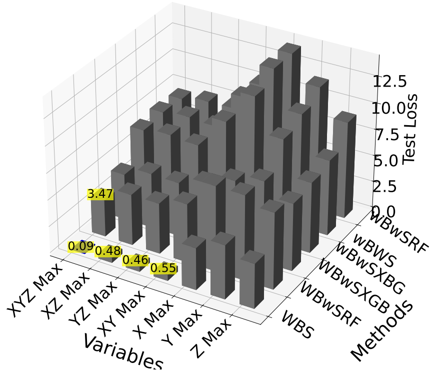
(b) Test Precision Max.



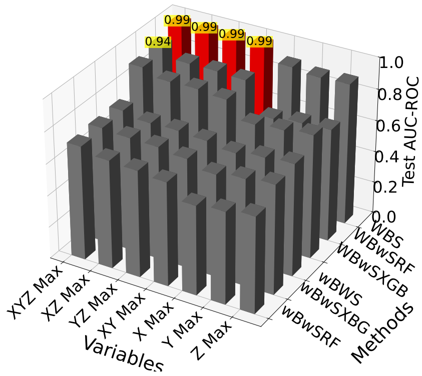
(c) Test Recall Max.



(d) Test F1 Score Max.



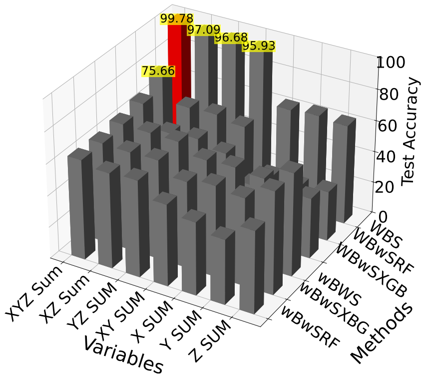
(e) Test Loss Max.



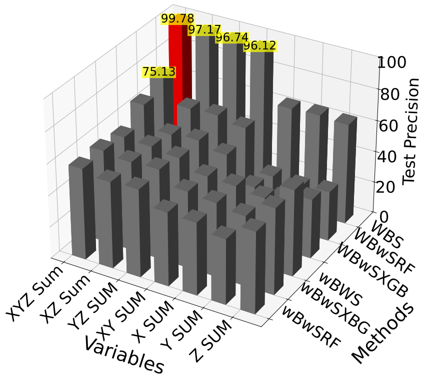
(f) Test AUC-ROC Max.

Fig. 7.2 Illustration of the performance metrics for Max case

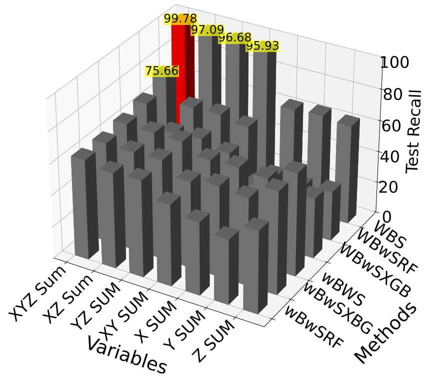
effectively captured vibration energy across all three axes. Furthermore, a one-sample t-test was performed to verify whether the mean test accuracy was statistically high for at least 95% of the time. The test accuracies for iterations were consistently high, yielding a mean accuracy of 99.774% with a standard deviation of 0.047%. The 95% confidence interval for the mean test accuracy was computed to be (99.761% and 99.787%). A t-statistic of 3.606 with a p-value of 0.0007 was observed, indicating statistical significance. Prediction accuracy was visualized using Kernel Density Estimation (KDE), with the mean accuracy and confidence interval. Figure 7.5 illustrates the density distribution of the test accuracies over the 50 iterations using kernel density estimation (KDE). The plot is annotated with



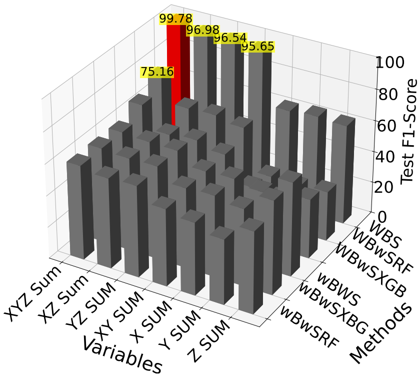
(a) Test Accuracy SUM.



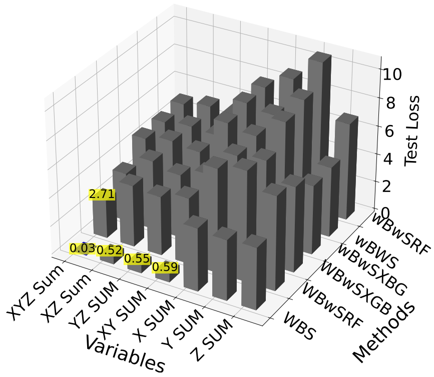
(b) Test Precision SUM.



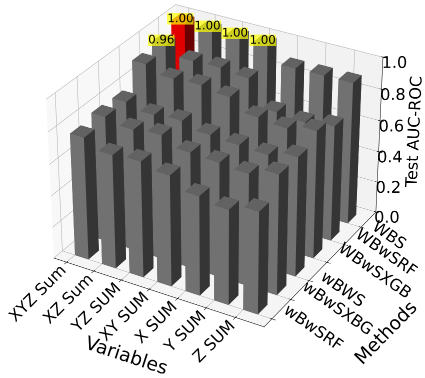
(c) Test Recall SUM.



(d) Test F1 Score SUM.



(e) Test Loss SUM .



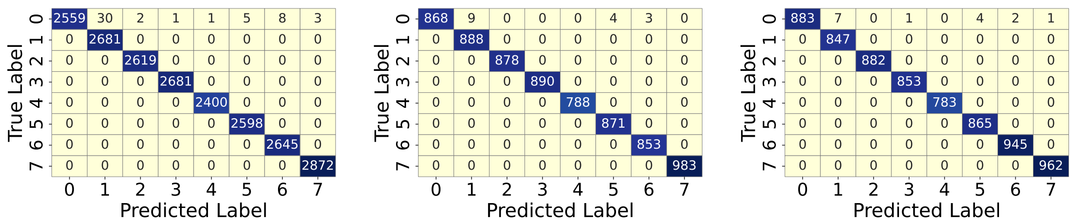
(f) Test AUC-ROC SUM.

Fig. 7.3 Illustration of the performance metrics for SUM case

the mean accuracy and the boundaries of the 95% confidence interval, visually confirming the high and consistent performance of the ensemble approach.

7.2.3 Test accuracy and model run time

The computer system recorded the total time for running all 126 sets, ensuring that no other tasks ran simultaneously. This recording was carried out to understand the use of resources for each set and find the best possible combination of test accuracy and total run time. Figure 7.6(a) displays a plot showing the test accuracy versus the total model run time. The x-axis represents 126 sets, while the y-axis shows two labels: test accuracy in Blue and running time in red, for clarity. This figure has too many values to understand;



(a) Training. (b) Validation. (c) Test.

Fig. 7.4 Illustration of the Confusion matrices for Set 85.

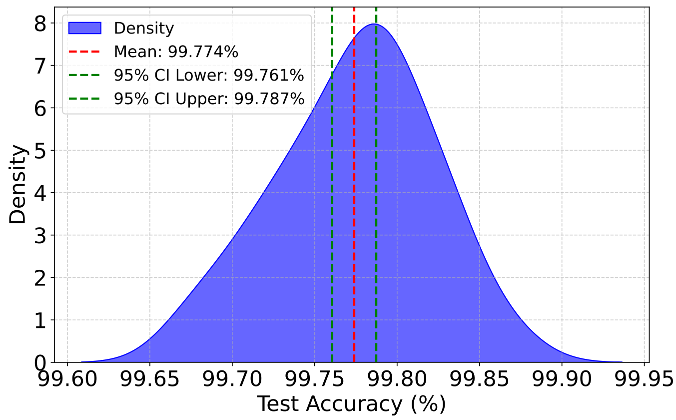
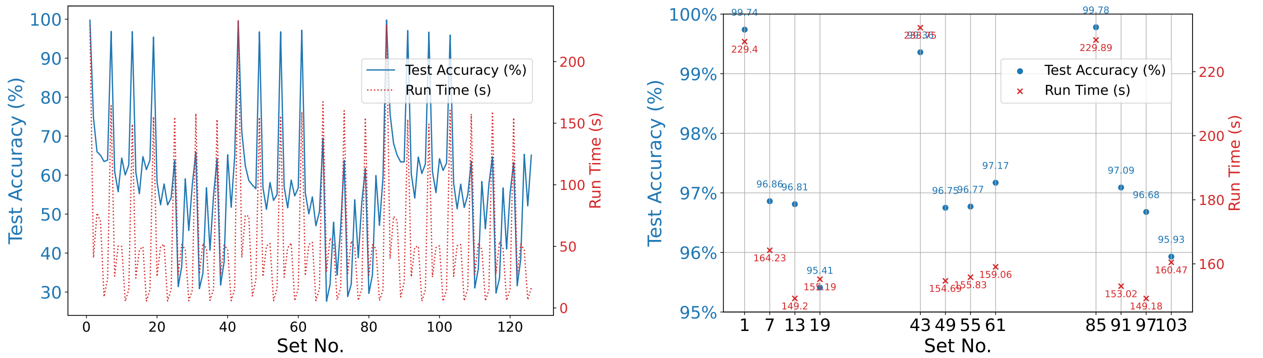


Fig. 7.5 Distribution of test accuracy over 50 iterations for Set 85.

for this one, more Figure 7.6(b) is plotted with only the highest test accuracies and their corresponding time values. The highest run time is 233.75 seconds for the set 43, having the third highest test accuracy of 99.36%. For the highest test accuracy of set no 85, the run time is 229.89 seconds, the 2^{nd} highest time across all the 126 sets.

7.3 Discussion

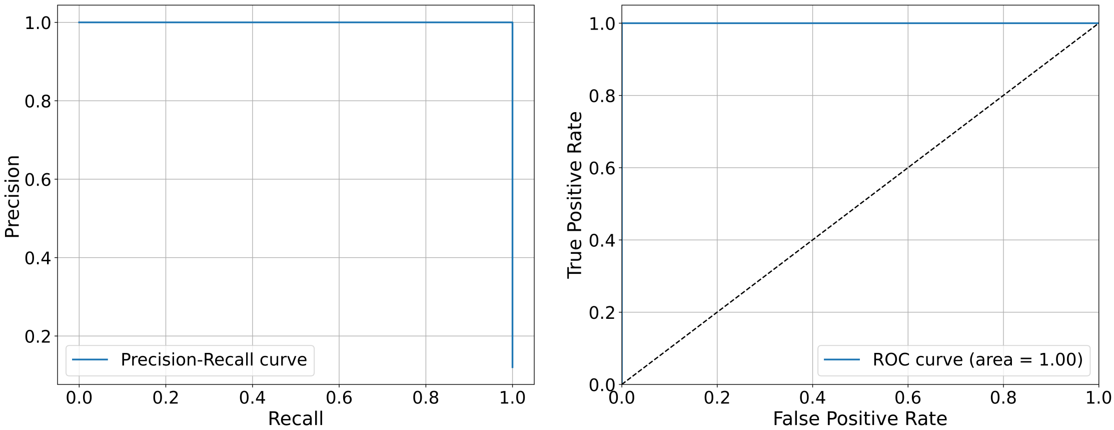
This section discusses the work's results and findings and explains the critical factors and aspects.



(a) Test accuracy *vs.* time for all model.

(b) Test accuracy *vs.* time for high-accuracy methods.

Fig. 7.6 Accuracy *vs.* time.



(a) Precision-Recall Curve.

(b) ROC Curve.

Fig. 7.7 Precision, Recall and ROC Curves for Set 85.

7.3.1 Performance matrices

This section discusses the performance of the proposed approach using different performance matrices.

7.3.1.1 Training, testing and validation

The performance metrics for vehicle classification were significantly influenced by the methods used for data balancing, classifier stacking and the selection of vibration signal features. The rationale behind these performances can be dissected based on the methods and features utilized. The test results are shown in the Figures 7.1, 7.2, 7.3 and the training and Validation matrices are shown in Tables 7.1, 7.2, 7.3.

7.3.1.2 Data balancing and classifier stacking

WBS method: The WBS method consistently demonstrated superior performance across all sets, incorporating data balancing using ADASYN and classifier stacking with Random Forest and XGBoost. ADASYN addresses class imbalance by generating synthetic samples for minority classes, creating a balanced dataset that allows the model to learn from all classes equally. Stacking classifiers combines the strengths of multiple models, leveraging their unique decision boundaries and error-reduction capabilities. This ensemble approach leads to enhanced pattern recognition and robustness. For instance, in set 1 (XYZ RMS values), the WBS method achieved a validation accuracy of 99.80% and a test accuracy of 99.74%, highlighting its ability to utilize vibration signal information effectively. The high AUC-ROC scores approx (1.00 for both validation and testing) indicate the model's good classification ability and the high F1-Scores (99.80% for validation and 99.74% for testing) reflect its balanced performance in terms of precision and recall. This highlights the method's ability to handle class imbalances and improve model robustness, ensuring accurate classification even for minority classes.

WBwSRF and WBwSXGB methods When data balancing was applied without stacking (WBwSRF and WBwSXGB), there were noticeable improvements over methods without balancing. However, they still need to reach the performance levels of the WBS method. For example, in set 2 (XYZ RMS values), WBwSRF achieved a validation accuracy of 75.71% and a test accuracy of 74.75%. WBwSXGB reached a validation accuracy of 66.44% and a test accuracy of 65.99%. While balancing reduced bias towards majority classes by ensuring that the model learned from underrepresented classes, the absence of stacking limited the models' capability to capture complex interactions and patterns in the data. This limitation is evident in the lower F1-Scores and AUC-ROC values compared to WBS, highlighting the importance of combining multiple classifiers to capture a broader range of data characteristics.

7.3.1.3 Performance without balancing and stacking

wBWS, wBwSRF and wBwSXGB methods: Methods without data balancing and stacking (wBWS, wBwSRF, wBwSXGB) showed significantly lower performance. For instance, in set 4 (XYZ RMS values), the wBWS method resulted in a validation accuracy of 64.01% and a test accuracy of 65.12%. The presence of class imbalance led to a bias towards the majority classes, causing the model to perform poorly on minority classes. Additionally, relying on a single classifier restricted the model's generalization ability, as it could not leverage the strengths of multiple learning algorithms. These methods' lower F1-Scores and AUC-ROC values indicate their poor generalization and discriminative abilities, confirming the necessity of balancing and stacking for robust model performance.

7.3.2 Impact of Feature Selection

7.3.2.1 Comprehensive directional features

Including all three directional features (X, Y, Z axes) generally led to higher performance than fewer features. In set 85, which used the SUM values of XYZ directions, the WBS method achieved a validation accuracy of 99.77% and a test accuracy of 99.78%. This indicates that utilizing all three directions ensures comprehensive information capture, crucial for distinguishing between different vehicle types. The high AUC-ROC score of 1.00 and F1-Score of 99.79% in testing underline the model's robustness and ability to generalize across various vehicle types and road conditions. The combination of these directional features captures the full range of vibration signals, enhancing the model's ability to detect subtle differences in the data.

7.3.2.2 Fewer features

Using fewer directional features (e.g., XY, XZ) resulted in slightly lower but still high performance with the WBS method. For example, the validation accuracy for XZ SUM values in set 91 was 97.33% and the test accuracy was 97.09%. While fewer features can still yield good results, including all three directions (XYZ) optimally captures the full range of vibration signal information, leading to better generalization. When using fewer features, the slightly lower F1-Scores and AUC-ROC values suggest that some information might need to be recovered, highlighting the importance of comprehensive feature selection for maximizing model performance.

Data balancing and classifier stacking are crucial for achieving high performance in vehicle classification. The WBS method consistently outperformed other methods, demonstrating robustness and effectiveness across training, validation and testing phases. Including comprehensive directional features further enhances the model's accuracy, ensuring reliable classification based on vibration signals. Incorporating all three directional components (XYZ) in variables such as SUM values was highly effective, capturing the full extent of the signal information and leading to superior performance metrics. This comprehensive approach ensures the model's robustness and generalization capability, making it a dependable tool for vehicle classification using road pavement vibration signals.

7.3.2.3 Highest performing set

Set 85 achieved the highest test accuracy of 99.78% due to ADASYN data balancing and a stacking classifier combining Random Forest and XGBoost. ADASYN addresses class imbalances by generating synthetic samples for minority classes, while the stacking classifier enhances pattern recognition by leveraging the strengths of both models. Additionally, using the SUM values across all XYZ directional vibration signals provides a comprehensive representation of the vehicle-induced vibrations, capturing the total energy of the vibration time series. This combination of advanced techniques and thorough feature selection led to the superior performance of Set 85.

7.3.2.4 Confusion matrices

Confusion matrices for the performing set 85 are shown in Figure 7.4 and demonstrate robust classification performance on training, testing and validation datasets. High values along the diagonal across all matrices indicate that most instances are correctly classified into their respective classes. This performance is partly due to the dominance of class 0, which represents trucks with 4391 instances, significantly more than other classes, some of which have fewer than 200 instances. The ADASYN data balancing technique was employed to address this imbalance, but some residual effects towards the majority class remain, leading to minor misclassifications.

This consistent yet minimal misclassification, particularly in class 0, reflects the model's strong learning capability and generalization across different datasets. Set 85 achieved a test accuracy of 99.78%, benefiting from including SUM values in all XYZ directions of the vibration signature, which encapsulates the total energy of the vibration time series signal.

7.3.2.5 Precision-recall and ROC curves

The precision-recall and ROC curves, as shown in Figure 7.7, further corroborate the model's exceptional performance. The precision-recall curve shows near-perfect precision and recall values, demonstrating the model's ability to maintain high precision with minimal false positives and high recall with minimal false negatives. Similarly, with an area under the curve (AUC) of 1.00, the ROC curve signifies ideal classification ability with high true positive and low false positive rates. These curves confirm the effectiveness of the data balancing and stacking classifier methods, which combined the modeling results from

Random Forest and XGBoost classifiers, highlighting the model's robustness and reliability in distinguishing between different vehicle classes, even in the case of an insignificant class imbalance.

7.3.3 Repeated Experimentation and Statistical Significance

The experimental findings indicate that the proposed vehicle classification model, configured with the XYZ SUM feature and the WBS method, consistently delivers good performance. The high mean test accuracy (99.774%) with a very low standard deviation (0.047%) supports the robustness of the approach

The performance of the proposed classifier is primarily attributed to the recording of vibration energy by the XYZ SUM feature, which integrates the contributions from all three axes. In addition, the use of ADASYN effectively mitigates class imbalance, ensuring that the model is not biased toward majority classes. The stacking ensemble, which combines the strengths of Random Forest and XGBoost via a meta-classifier, further enhances predictive accuracy by reducing bias and variance.

The statistical analysis reinforces these observations. A one-sample t-test confirmed that the observed mean accuracy is statistically significantly higher than the benchmark value. Together, these results demonstrate that the integrated approach is scientifically and technically robust, ensuring reliable vehicle classification performance suitable for practical deployment.

7.3.4 Model run time analysis and performance evaluation

The model run times for the various sets in the vehicle classification study varied significantly, reflecting the complexity and computational demands of each method and variable combination. The run times ranged from as low as 5.42 seconds for simpler models to as high as 233.75 seconds for more complex models incorporating extensive features and advanced techniques.

For instance, Set 1, which utilized the XYZ RMS values with the WBS method, had a run time of 229.40 seconds, achieving a test accuracy of 99.74%, training accuracy of 99.66% and validation accuracy of 99.80%. Similarly, Set 85, employing the SUM values across XYZ directions with the same WBS method, took 229.89 seconds, achieving the highest test accuracy of 99.78%, training accuracy of 99.76% and validation accuracy of 99.787%. These longer run times indicate the computational effort required to process and analyze the comprehensive feature sets and perform data balancing and classifier stacking. The use of ADASYN for data balancing and the implementation of stacking classifiers (Random Forest and XGBoost) contribute to the increased computational load, as these techniques involve generating synthetic samples and combining multiple models to enhance performance.

In contrast, methods without data balancing and stacking, such as Set 2 (XYZ RMS values with WBwSRF), had much shorter run times of 40.82 seconds, with lower performance metrics: a test accuracy of 74.75%, training accuracy of 100.00% and validation accuracy of 75.71%. This reflects the reduced computational complexity when simpler models and fewer pre-processing steps are involved. Additionally, models using fewer directional features, such as Set 26 (X RMS with WBwSRF), demonstrated shorter run times of 26.95 seconds, highlighting the impact of feature selection on computational demands. More straightforward methods and fewer features reduce the amount of data that needs to be processed, leading to faster run times but at the cost of lower accuracy.

The extensive use of ADASYN for data balancing and the implementation of stacking classifiers significantly contribute to the more extended run times observed in the highest-performing sets. However, this increase in computational time is justified by the substantial improvements in classification accuracy and robustness. These methods effectively address class imbalance and leverage the strengths of multiple classifiers, resulting in superior performance metrics.

While the advanced techniques employed in sets like Set 85 result in longer run times, the substantial gains in accuracy and model reliability underscore the importance of balancing computational efficiency with performance. The comprehensive feature sets and sophisticated methods ensure the highest possible accuracy in vehicle classification, demonstrating the trade-off between computational complexity and model performance. The increased run times are a necessary trade-off for achieving high accuracy, robustness and reliable classification outcomes.

The evaluation of vehicle classification models demonstrates the importance of data balancing, feature selection and classifier stacking. The WBS method, utilizing ADASYN and a combination of Random Forest and XGBoost classifiers, consistently achieved high performance across training, validation and testing phases. Set 85 (XYZ SUM) achieved the highest test accuracy of 99.78%. The confusion matrices and ROC curves show that the models can classify different types of vehicles accurately. The precision-recall curves confirm high recall and precision values, indicating that the models perform well even with imbalanced data. When analyzing the model run time, it was found that there is a trade-off between computational time and accuracy. While WBS methods take longer to run, they deliver better results. Efficient use of features and effective data balancing significantly improve model performance, highlighting the importance of comprehensive approaches in vehicle classification tasks.

The proposed algorithm demonstrates high classification accuracy, exceeding 99%, making it a reliable approach for vehicle classification using road-induced vibrations. Its key advantages include eliminating the need for cameras, reducing privacy concerns and maintaining a relatively low-cost implementation using a single tri-axial accelerometer. Additionally, the model is robust in handling imbalanced datasets by applying ADASYN oversampling. However, certain limitations exist. The algorithm's performance depends on single-vehicle pass-by conditions, which may limit its applicability in dense traffic scenarios. Moreover, variations in pavement conditions and environmental factors may necessitate periodic recalibration to maintain accuracy. Future research could focus on adaptive modeling techniques to enhance generalization across diverse roadway conditions and mixed-traffic environments.

7.4 Conclusions

Accurate vehicle classification is essential for traffic monitoring, infrastructure management and autonomous vehicle systems. Existing methods often struggle with class imbalances and lack robustness, motivating the objective of this study to develop a more accurate and economical vehicle classification system. This study utilized a hardware setup comprising a high-frequency sampling accelerometer to capture road vibrations. The captured signals were pre-processed through data cleaning and segmentation into uniform windows. Signal processing techniques were applied to extract features such as RMS, Max and SUM values of vibrations across XYZ axes. Various machine learning methods, including Random Forest and XGBoost, were employed to develop and test the classification models with and without data balancing and classifier stacking. The results demonstrated that the WBS method (using ADASYN for data balancing and stacking classifiers) achieved the highest accuracy. Set 85 (XYZ SUM values) yielded a test accuracy of 99.78% with a 3-D accelerometer. This approach is both practical and economical, especially when utilizing a 2-D accelerometer, which reduces the hardware complexity by using one less channel while maintaining a high test accuracy of 96.86%. Additionally, the 2-D accelerometer data still captures sufficient information for robust vehicle classification. This research shows that a highly accurate vehicle classification system can be developed with elaborate accelerometer data, feature engineering, data balancing and model stacking.

The experimental evaluation over 50 iterations demonstrates that the proposed vehicle classification model, leveraging the XYZ SUM feature and the WBS method, achieves exceptionally high and consistent performance with a mean test accuracy of 99.774%. The low variability, as indicated by a standard deviation of 0.047% and a narrow 95% confidence interval, confirms the robustness of the approach. Effective class balancing via ADASYN Random Forest and XGBoost integration through stacking significantly reduces bias and variance. Overall, the results validate that the integrated method is both scientifically sound and technically robust, making it a promising solution for vehicle classification in real-world applications

Beyond achieving high classification accuracy, the proposed system offers several practical advantages. Its reliance on accelerometer-based sensing ensures a scalable, cost-effective solution that requires minimal infrastructure modifications. Unlike vision-based approaches, it remains unaffected by lighting conditions and occlusions, making it highly adaptable to real-world deployment scenarios. Furthermore, integrating ADASYN-based data balancing and stacking classifiers enhances model generalization across diverse road conditions and vehicle types. These benefits make the proposed approach a promising alternative for large-scale traffic monitoring, smart infrastructure planning and intelligent transportation systems.

This study lays the groundwork for vehicle classification using road vibration input to accelerometer sensors and machine learning. This complex process increases the time required for model running, which can be reduced if the data points of all vehicle classes are in the same range. Non-motorized vehicle types are not considered for this study, but this can be done in further studies. This study collected the data for a single vehicle pass-by; in further studies, more than one vehicle simultaneously passing by data can also be utilized. The data collection was carried out in dry pavement conditions for winter and summer, so there is scope to carry out this study further for wet pavement. This study was conducted on bituminous road pavement; the same study can also be validated on concrete pavement. Integrating automatic traffic management, which this study can use in decision-making, such as channeling the traffic and maintaining non-heavy vehicle zones. This study can help analyze traffic patterns and reduce accidents and collisions, enhancing road safety. The vibration signature is directly connected to the vehicle weight; if the weight of the vehicles is also tagged, then overloaded vehicles can be detected using these sensors for different pavement conditions. First, it will detect the vehicle type using the present study and then, from the permissible load, it will alert the authorities to overloading.

The vehicle classification framework developed in this chapter enables real-time identification of traffic composition based on ground vibration signals. This classified vehicle stream, categorized by type and frequency, serves as a critical input for the subsequent forecasting and route optimization framework. The chapter 8 utilizes this output to predict classified vehicle volume and identify vibration-optimal routes, particularly in sensitive urban corridors.