Chapter 5

DISCUSSIONS

5.1 Discussion based on the results obtained for machine learning

The experiments were conducted with five different machine learning algorithms: Naive Bayes, Jrip, Multilayer perception), PART, SMO, and Random Forest on the original and the reduced datasets containing pillar stability for case 1. The original datasets were composed of all the given features where we experimented.

Most datasets usually comprised a certain amount of redundancy that does not assist knowledge discovery and may mislead the entire process. The objective of this phase was to find valuable features to represent the entire data and eliminate non-relevant features. This step also helps in saving time during the data processing and improving the interpretability of data.

Firstly, we have applied fuzzy rough feature selection based on the rank search to reduce datasets by removing irrelevant and redundant features. Entire experiments were performed based on the percentage split of 80:20. The confusion matrix was obtained for Naive Bayes, Jrip, Multilayer perception, PART, SMO, and Random Forest models to assess their capability of correct classification. With count values segregated by class, the correct and incorrect predictions were constructed. To train and evaluate classifier performance, the original dataset was divided into training and testing sets.

The Naive Bayes classification model (Table 4.1) correctly predicted 12 out of 14 stable cases, 7 out of 9 unstable cases, and 8 out of 13 failed cases. The SMO classification model (Table 4.2) correctly predicted 12 out of 14 stable cases, 7 out of 9 unstable cases, and 9 out of 13 failed cases.

The Jrip classification model (Table 4.3) correctly predicted 11 out of 14 stable cases, 7 out of 9 unstable cases, and 8 out of 13 failed cases. The PART classification model (Table 4.4) correctly predicted stable 7 out of 14 cases, 8 out of 9 unstable cases, and 10 out of 13 failed cases. The RF classification model (Table 4.5) correctly predicted 12 out of 14 stable cases, 7 out of 9 unstable cases, and 9 out of 13 failed cases.

On the reduced datasets, the Navie Bayes model correctly predicted 12 out of 14 stable cases, 7 out of 9 unstable cases, and 9 out of 13 failed cases (Table 4.6). The SMO model correctly predicted 13 out of 14 stable cases, 7 out of 9 unstable cases, and 9 out of 13 failed cases (Table 4.7). The Jrip classification model correctly predicted 11 out of 14 stable cases, 7 out of 9 unstable cases, and 9 out of 13 failed cases (Table 4.8). The PART classification model correctly predicted 13 out of 14 stable cases, 7 out of 9 unstable cases, and 8 out of 13 failed cases (Table 4.9). The RF classification model correctly predicted 12 out of 14 stable cases, 7 out of 9 unstable cases, and 11 out of 13 failed cases (Table 4.10). Although the prediction of all the classification models is satisfactory, the best performance was obtained by RF.

The performance metrics for the different machine learning tools on original datasets are given in Table 4.11. The minimum accuracy was in the case of PART model (69.4%), while the RF showed the maximum accuracy of 77.8%.

The performance metrics for the different machine learning tools on reduced datasets are given in table 4.12. The minimum accuracy of 75% was obtained for the Jrip model, while the RF model showed the highest accuracy of 83.3%. The AUC and MCC of the RF model were almost near one, which signified the best predictor.

Table 4.13 shows the ranking of different features on the fuzzy rough feature selection. The most important feature predicted was the w/h ratio with the rank value of 0.04185 followed by pillar strength to pillar stress with the rank value of 0.02747, UCS having the rank value of 0.00745, and pillar stress with the rank value of 0.00566.

The ROC curves were created in order to provide a visual representation of the classifier in the form of a plot of false-positive rate (x-axis) vs true positive rate (y-axis) (y-axis). The area under the ROC curve (AUC) was rated as 'outstanding' for AUC values of 0.9-1, 'good' for AUC values of 0.8-0.9, 'fair' for AUC values of 0.7-0.8, 'poor' for AUC values of 0.6-0.7, and failed for AUC values of 0.5-0.6. The AUC measures how well the model differentiates between positive and negative classifications. The higher score of the classifier's AUC score indicated a better distinguishing between positive and negative classes. In this study, the RF model got an AUC of 0.934 for the original dataset and 0.920 for the reduced data set (Table 11-12). The visual representation of the models is shown in Figure 4.1 for the original and Figure 4.2 for the reduced datasets.

5.2 Discussions based on the results obtained by PCA and SSE Techniques

The PCA technique selected two parameters, Pillar Width(W) to Pillar Height(H) ratio and Uniaxial Compressive Strength (UCS), out of the seven parameters. It shows that the W/H ratio and UCS prominently affect the pillar strength. On the other hand, the

SSE technique selected Pillar Width (W), Pillar Height (H), and Uniaxial Compressive Strength (UCS).

It was observed that both PCA and SSE techniques selected pillar width (W), pillar height (H), and uniaxial compressive strength (UCS) as the most influential parameters for the prediction of pillar strength.

The R^2 and standard error of estimate (SEE) for the model developed by the PCA were 0.86 and 0.112, respectively. The model developed by SSE had R^2 of 0.84 and SEE of 0.123. Almost similar values of R^2 and standard error of estimate for the two models showed that there is no significant difference in accuracy in prediction of PS by PCA and SSE, rather, the values of SSE are slightly inferior to the values of PCA. PCA technique has more accuracy in predicting PS than the SSE technique. The comparison curve of pillar strength (PS) with the values obtained by the developed PCA (PS PCA) and SSE models (PS SSE) have been shown in Figure 5.1.

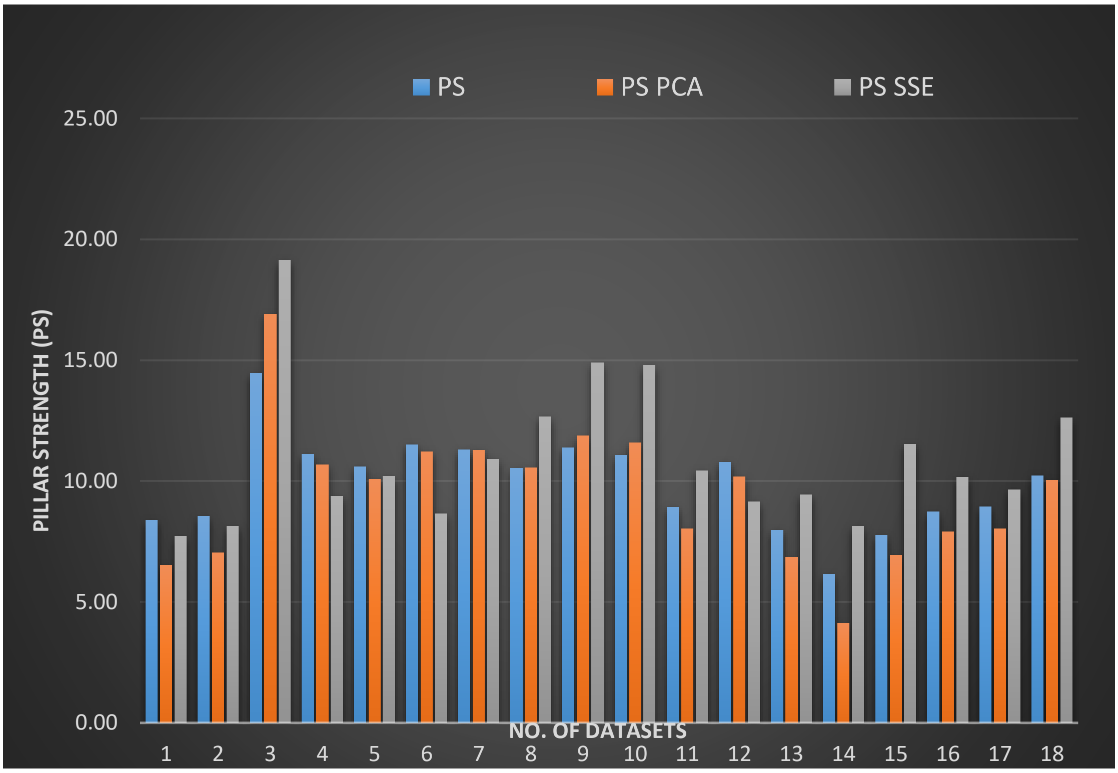

Figure 5.1: Comparison curve of PCA and SSE with theoretical pillar strength

From the above comparison, it was observed that the pillar strength obtained by the PCA model are almost identical to the theoretical values of PS. On the other hand, the values obtained by SSE has slightly deviated from the theoretical values. It confirmed the better accuracy of PCA over the SSE technique in predicting pillar strength.

5.3 Validations

The factor of safety (FoS) has been estimated based on the model developed by PCA and SSE for pillar strength (Table 5.2). It was observed that the values obtained by the PCA based model are almost identical to the theoretical values of factor of safety (FoS). Although the values obtained by the SSE model are also close to the theoretical values, the values of the PCA model are more accurate than the SSE model (Fig. 5.2).

Table 5.1 Datasets for validation of developed models.

SL. No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	D	**W**	**B**	**H**	**W/H**	**UCS**	**PL OBS**	**D/250**	**PS (Eq. 3.2)**	**FoS (9/7)**	**PS PCA**	**PS SSE**	**FOS PCA**	**FOS SSE**
1	70	9	3	3	3	32	3.1	0.28	8.38	2.69	6.52	7.71	2.1	2.48
2	65	10	3	3	3.1	33	3.4	0.26	8.54	2.52	7.03	8.12	2.1	2.4
3	60	12	3	3	6.5	42	3.9	0.24	14.46	3.71	16.91	19.13	4.3	4.91
4	65	12	3	3	3.8	43	3.6	0.26	11.1	3.1	10.68	9.37	3	2.62
5	65	12	3	3	4	38	3.6	0.26	10.6	2.96	10.06	10.19	2.8	2.85
6	65	12	3	3	3.5	48	3.6	0.26	11.49	3.21	11.22	8.66	3.1	2.42
7	65	14	3	3	4.2	41	4.3	0.26	11.29	2.61	11.28	10.9	2.6	2.52
8	70	14	3	3	5	29	4	0.28	10.52	2.65	10.55	12.67	2.7	3.2
9	75	15	4	3	5.8	27	4	0.3	11.38	2.81	11.87	14.89	2.9	3.68
10	75	15	4	3	5.8	26	4.3	0.3	11.08	2.59	11.58	14.78	2.7	3.46
11	55	12	3	3	3.8	30	3.6	0.22	8.91	2.5	8.03	10.43	2.3	2.92
12	55	11	3	3	3.4	44	3.3	0.22	10.79	3.24	10.17	9.14	3.1	2.75
13	60	12	3	3	3.5	28	4.2	0.24	7.97	1.91	6.84	9.44	1.6	2.27
14	60	10	3	3	3.1	20	3.1	0.24	6.13	1.96	4.12	8.12	1.3	2.59
15	55	13	3	3	4.2	21	4.1	0.22	7.75	1.9	6.93	11.52	1.7	2.82
16	55	12	3	3	3.8	30	3.8	0.22	8.74	2.29	7.9	10.16	2.1	2.66
17	55	12	3	3	3.6	33	3.6	0.22	8.94	2.5	8.02	9.65	2.3	2.7
18	65	14	3	3	4.5	32	5.5	0.26	10.23	1.87	10.03	12.61	1.8	2.31

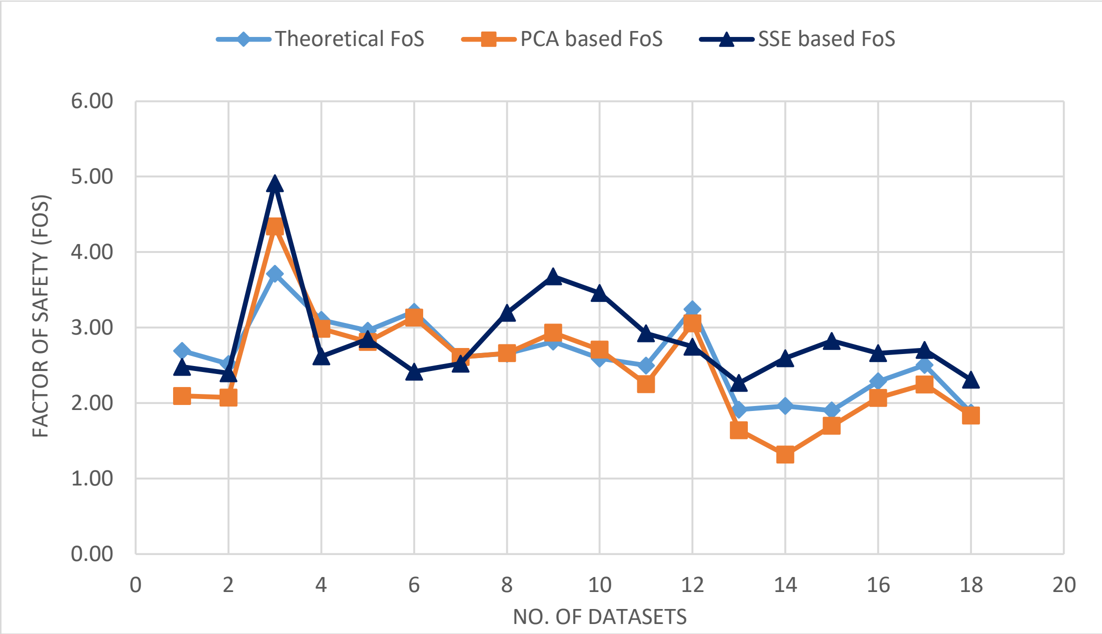

Figure 5.2: Comparison curve for the factor of safety (FoS)