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Forearm Orientation and Muscle Force Invariant Feature Selection Method for Myoelectric Pattern Recognition

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ABSTRACT Electromyogram (EMG) signal-based prosthetic hand can restore an amputee's missing functionalities, which requires a faithful electromyogram pattern recognition (EMG-PR) system. However, forearm orientation and muscle force variation make the EMG-PR system more complex, and the problem becomes more complicated when muscle force levels and forearm orientations arise simultaneously. The problems can be minimized using a more significant number of features or high-density surface EMG, but it increases design complexity and needs higher computational power. In this regard, we have proposed a feature selection method that selects both feature and channel simultaneously. The proposed feature selection method selects only 7 to 20 features among 162 features with comparable or better performance. In this study, these selected features achieve a significant improvement in the accuracy, sensitivity, specificity, precision, F1 score, and Matthew correlation coefficient (MCC) by 3.18% to 4.28%, 9.14% to 12.85%, 1.83% to 2.57%, 8.30% to 10.99%, 9.22% to 13.92%, and 0.11 to 0.15, respectively comparing with four existing feature selection methods. In this research, the proposed feature selection method achieves a forearm orientation and muscle force invariant F1 score of 91.46% for training the k- nearest neighbor (KNN) classifier with two orientations, wrist fully supinated (O1) and wrist fully pronated (O3), with a medium force level. We have also achieved an F1 score of 93.27% for training the KNN classifier with all orientations with a medium force level. So, the proposed feature selection method would be very much helpful for finding the least dimensional features and achieving improved EMG-PR performance with multiple limiting factors.

INDEX TERMS EMG pattern recognition, feature selection, forearm orientation, muscle force variation.

I. INTRODUCTION

Limb loss limits individuals from performing their daily activities, causing them to be considered a burden to society. A survey carried out in the United States in 2005 indicates that approximately 1.6 million people were suffering from limb loss, and the number of amputees may be increased to 3.6 million by 2050 [1]. Another survey in England reveals that about 6000 people get amputees each year; roughly a fifth is upper limb amputee [2]. Researchers focus on this growing issue to develop a prosthetic arm with higher degrees of freedom. In the meantime, advanced prosthetic arms are commercially available, including COAPT [3], Open Bionics [4], and Ottobock [5]. The modern prosthetic arms utilize EMG signals collected from remaining hand muscles using a surface electrode or capacitive electrode [6]–[10].

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FIGURE 1. Three forearm orientations for EMG data collection. Source: Electromyogram (EMG) repository (rami-khushaba.com) (accessed on 06 Feb 2022).

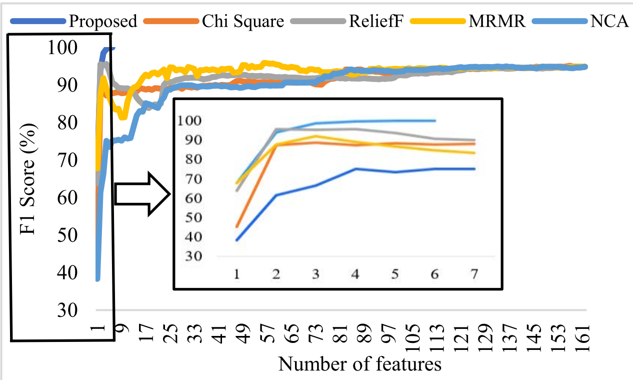
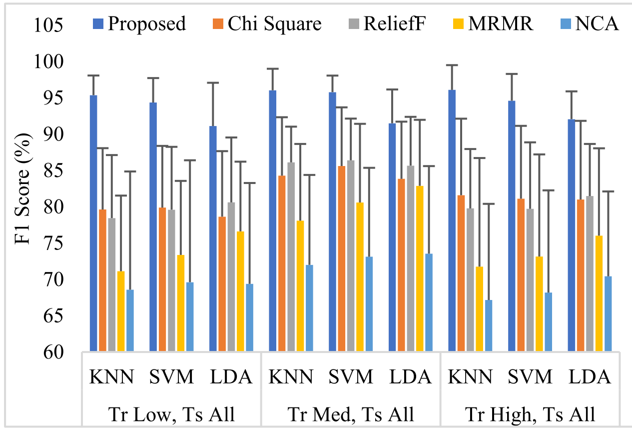
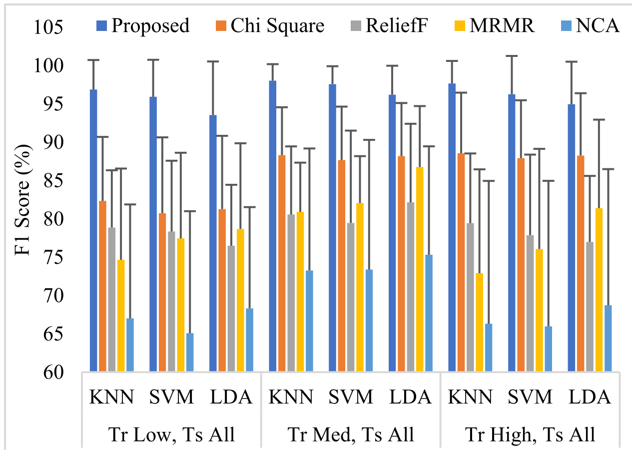


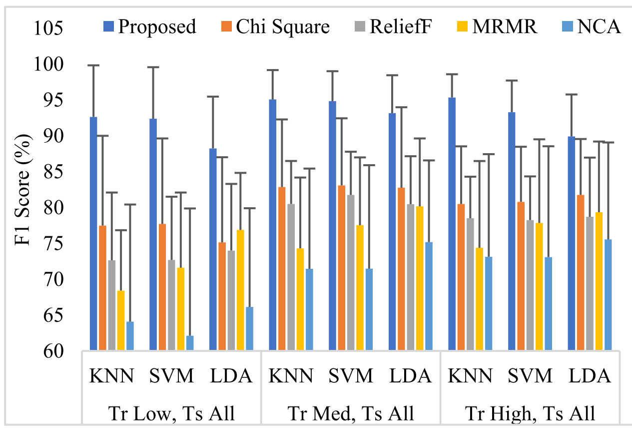
FIGURE 2. The EMG-PR performance using KNN classifier with the number of features and different feature selection methods.



(a) Training and testing for O1



(b) Training and testing for O2



(c) Training and testing for O3

FIGURE 3. The F1 scores of different feature selection methods when the classifiers are trained for one orientation with one force level and tested for trained orientation with all force levels.

Further, features are extracted, and the intended movements are predicted by a classifier [2], [11]. However, the available prosthetic arms are not commercially successful due to several limiting factors including electrode position shift [12], [13], variation of muscle contraction force [14]–[16], limb position [17], [18], forearm orientation [19], [20], mobility of subject [21], and multiday variation [22], [23]. These factors make significant alterations in EMG signal properties, i.e., time-domain and frequency-domain properties, and make changes in extracted features [14], [19], [23]. Consequently, the factors significantly degrade the EMG-PR performance [21]. In addition, the achievement of satisfactory EMG-PR performance becomes quite challenging when multiple factors arise simultaneously.

In an attempt to resolve multiple limiting factors simultaneously, a few pieces of research have been found over the last decades. Khushaba *et al.* [20] employed 39-dimensional feature space employing time-domain power spectral descriptors and showed that co-factors, forearm orientation, and muscle contraction force degrade the EMG-PR performance drastically. Finally, they recommended utilizing all orientations with a medium force level for training to achieve satisfactory performance of 91%. Further, Rajapriya *et al.* [19] proposed a wavelet bispectrum-based feature extraction method to resolve forearm orientation and muscle force variation. They achieved 90.35% EMG-PR performance using 96-dimensional feature space, all orientations, and a medium force level for training in this study. In addition, Asogbon *et al.* [21] also proposed a feature extraction method, invariant time-domain descriptor, to resolve muscle force variation and subject mobility. They employed a 40-dimensional feature space with a medium force level to achieve 84% to 93% EMG-PR performance. In addition

TABLE 1. The EMG-PR performances of different feature selection methods when the classifiers are trained for O1 with one force level and tested for trained orientation with all force levels.

	Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Training with low force	Accuracy	KNN	98.45±0.91	93.35±2.73	92.95±2.87	90.67±3.41	89.78±5.28
		SVM	98.13±1.12	93.48±2.66	93.38±2.80	91.50±3.33	90.25±5.38
		LDA	97.09±1.92	93.02±2.84	93.69±2.95	92.56±3.03	90.15±4.56
	Sensitivity	KNN	95.36±2.72	80.05±8.18	78.84±8.62	72.02±10.24	69.33±15.85
		SVM	94.39±3.36	80.44±7.99	80.14±8.39	74.51±9.99	70.74±16.13
		LDA	91.27±5.75	79.07±8.51	81.06±8.85	77.69±9.10	70.44±13.69
	Specificity	KNN	99.07±0.54	96.01±1.64	95.77±1.72	94.40±2.05	93.87±3.17
		SVM	98.88±0.67	96.09±1.60	96.03±1.68	94.90±2.00	94.15±3.23
		LDA	98.25±1.15	95.81±1.70	96.21±1.77	95.54±1.82	94.09±2.74
	Precision	KNN	95.61±2.54	82.63±7.67	81.83±8.09	74.26±9.07	72.25±16.06
		SVM	94.87±3.04	82.55±6.96	82.77±7.37	76.97±8.60	73.52±16.28
		LDA	92.12±5.30	81.05±8.41	83.38±8.42	80.02±7.54	73.5±13.31
	F1 Score	KNN	95.36±2.71	79.62±8.45	78.44±8.68	71.12±10.42	68.58±16.28
		SVM	94.35±3.37	79.88±8.50	79.59±8.66	73.37±10.19	69.61±16.79
		LDA	91.11±5.96	78.63±9.03	80.60±8.94	76.61±9.60	69.38±13.89
	MCC	KNN	0.95±0.03	0.77±0.1	0.76±0.1	0.67±0.12	0.62±0.16
		SVM	0.91±0.05	0.77±0.09	0.77±0.1	0.7±0.11	0.63±0.17
		LDA	0.87±0.08	0.75±0.1	0.78±0.1	0.74±0.1	0.63±0.15
Training with medium force	Accuracy	KNN	98.69±0.97	94.87±2.57	95.45±1.61	92.75±3.52	90.80±4.14
		SVM	98.60±0.75	95.33±2.60	95.54±1.87	93.62±3.60	91.21±4.08
		LDA	97.19±1.54	94.73±2.48	95.29±2.24	94.39±3.07	91.33±3.98
	Sensitivity	KNN	96.06±2.91	84.61±7.71	86.34±4.84	78.24±10.55	72.40±12.43
		SVM	95.81±2.25	85.98±7.8	86.61±5.62	80.86±10.8	73.63±12.23
		LDA	91.58±4.62	84.19±7.43	85.86±6.72	83.16±9.2	73.99±11.95
	Specificity	KNN	99.21±0.58	96.92±1.54	97.27±0.97	95.65±2.11	94.48±2.49
		SVM	99.16±0.45	97.20±1.56	97.32±1.12	96.17±2.16	94.73±2.45
		LDA	98.32±0.92	96.84±1.49	97.17±1.34	96.63±1.84	94.80±2.39
	Precision	KNN	96.36±2.53	86.18±6.58	87.51±4.76	79.53±10.12	74.42±11.67
		SVM	96.15±1.99	87.26±6.92	87.91±5.30	81.77±10.89	75.66±11.48
		LDA	92.63±4.12	85.89±6.98	87.38±6.28	84.38±8.57	75.86±10.72
	F1 Score	KNN	96.03±2.97	84.28±8.05	86.11±4.92	78.08±10.57	72.00±12.38
		SVM	95.78±2.28	85.61±8.08	86.39±5.75	80.59±10.83	73.12±12.24
		LDA	91.49±4.66	83.84±7.88	85.66±6.72	82.88±9.09	73.54±12.06
	MCC	KNN	0.95±0.03	0.82±0.09	0.84±0.06	0.74±0.12	0.72±0.17
		SVM	0.94±0.03	0.84±0.09	0.84±0.07	0.77±0.13	0.74±0.17
		LDA	0.88±0.07	0.82±0.09	0.84±0.08	0.80±0.11	0.74±0.13
Training with high force	Accuracy	KNN	98.71±1.12	94.01±3.44	93.32±2.77	90.63±4.92	89.19±4.34
		SVM	98.22±1.21	93.87±3.27	93.31±3.07	91.22±4.49	89.69±4.36
		LDA	97.39±1.27	93.84±3.40	93.94±2.41	92.16±3.95	90.32±3.88
	Sensitivity	KNN	96.12±3.36	82.02±10.32	79.97±8.32	71.88±14.76	67.57±13.03
		SVM	94.66±3.62	81.60±9.81	79.93±9.22	73.67±13.47	69.06±13.07
		LDA	92.16±3.82	81.53±10.21	81.82±7.23	76.47±11.85	70.96±11.63
	Specificity	KNN	99.22±0.67	96.40±2.06	95.99±1.66	94.38±2.95	93.51±2.61
		SVM	98.93±0.72	96.32±1.96	95.99±1.84	94.73±2.69	93.81±2.61
		LDA	98.43±0.76	96.31±2.04	96.36±1.45	95.29±2.37	94.19±2.33
	Precision	KNN	96.52±2.91	84.28±8.80	82.77±7.34	74.61±14.27	72.41±12.64
		SVM	95.14±3.21	84.25±8.30	82.84±7.89	75.98±13.5	73.05±13.03
		LDA	92.95±3.44	84.67±8.62	84.91±6.16	78.89±11.79	73.95±11.71
	F1 Score	KNN	96.09±3.41	81.59±10.54	79.77±8.18	71.76±14.95	67.16±13.24
		SVM	94.60±3.69	81.11±10.03	79.72±9.15	73.15±14.06	68.18±14.08
		LDA	92.06±3.83	81.00±10.83	81.47±7.18	76.02±12.03	70.42±11.69
	MCC	KNN	0.95±0.04	0.79±0.12	0.77±0.10	0.67±0.18	0.65±0.17
		SVM	0.92±0.04	0.79±0.11	0.77±0.11	0.69±0.16	0.67±0.17
		LDA	0.88±0.05	0.79±0.12	0.79±0.08	0.73±0.14	0.67±0.16

TABLE 1. *(Continued.)* **The EMG-PR performances of different feature selection methods when the classifiers are trained for O2 with one force level and tested for trained orientation with all force levels.**

	Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Training with low force	Accuracy	KNN	98.95±1.30	94.28±2.73	93.08±2.44	91.54±4.12	89.28±4.96
		SVM	98.63±1.64	93.84±3.17	93.06±2.72	92.55±3.87	88.90±4.98
		LDA	97.82±2.38	93.98±3.12	92.34±2.65	92.94±3.81	89.78±4.35
	Sensitivity	KNN	96.86±3.89	82.85±8.19	79.24±7.32	74.63±12.36	67.84±14.89
		SVM	95.88±4.91	81.51±9.52	79.18±8.17	77.65±11.61	66.70±14.95
		LDA	93.47±7.15	81.95±9.37	77.02±7.94	78.82±11.42	69.34±13.06
	Specificity	KNN	99.37±0.78	96.57±1.64	95.85±1.46	94.93±2.47	93.57±2.98
		SVM	99.18±0.98	96.30±1.90	95.84±1.63	95.53±2.32	93.34±2.99
		LDA	98.69±1.43	96.39±1.87	95.40±1.59	95.76±2.28	93.87±2.61
	Precision	KNN	97.17±3.44	86.58±6.33	81.56±6.34	79.65±9.52	70.33±14.37
		SVM	96.44±4.02	85.78±7.37	80.95±8.96	81.62±9.25	68.54±16.31
		LDA	94.61±5.51	85.05±8.22	79.26±6.64	82.57±9.21	72.57±12.44
	F1 Score	KNN	96.87±3.85	82.33±8.36	78.86±7.48	74.65±11.91	67.01±14.87
		SVM	95.92±4.83	80.74±9.89	78.34±9.24	77.45±11.17	65.08±15.92
		LDA	93.54±6.99	81.27±9.56	76.49±7.95	78.68±11.18	68.32±13.21
	F1 Score	KNN	0.96±0.04	0.81±0.09	0.76±0.08	0.71±0.14	0.64±0.17
		SVM	0.94±0.06	0.79±0.11	0.76±0.10	0.75±0.13	0.63±0.18
		LDA	0.90±0.08	0.79±0.11	0.73±0.09	0.76±0.13	0.66±0.15
Training with medium force	Accuracy	KNN	99.34±0.73	96.16±2.09	93.66±2.93	93.68±2.15	91.31±5.12
		SVM	99.19±0.78	95.97±2.32	93.45±3.61	94.17±1.99	91.51±5.20
		LDA	98.72±1.29	96.14±2.26	94.05±3.49	95.60±2.61	91.94±4.67
	Sensitivity	KNN	98.01±2.18	88.49±6.27	80.99±8.78	81.04±6.46	73.92±15.36
		SVM	97.57±2.35	87.91±6.95	80.34±10.82	82.52±5.98	74.53±15.6
		LDA	96.15±3.87	88.43±6.77	82.16±10.48	86.79±7.84	75.82±14.0
	Specificity	KNN	99.60±0.44	97.70±1.25	96.20±1.76	96.21±1.29	94.78±3.07
		SVM	99.51±0.47	97.58±1.39	96.07±2.16	96.50±1.20	94.91±3.12
		LDA	99.23±0.77	97.69±1.35	96.43±2.10	97.36±1.57	95.16±2.80
	Precision	KNN	98.14±1.99	89.84±5.40	82.35±8.84	82.16±6.20	74.92±16.38
		SVM	97.78±2.04	89.41±5.95	81.96±10.58	83.55±5.88	75.46±17.28
		LDA	96.75±3.06	89.56±6.27	83.93±9.62	88.16±7.57	77.14±14.33
	F1 Score	KNN	98.02±2.16	88.31±6.25	80.56±8.89	80.91±6.42	73.26±15.92
		SVM	97.58±2.33	87.66±6.98	79.46±12.05	82.07±6.11	73.38±16.92
		LDA	96.19±3.78	88.18±6.93	82.15±10.25	86.76±7.95	75.32±14.14
	MCC	KNN	0.98±0.03	0.87±0.07	0.78±0.11	0.78±0.08	0.67±0.21
		SVM	0.96±0.03	0.86±0.08	0.77±0.13	0.79±0.07	0.68±0.21
		LDA	0.94±0.04	0.86±0.08	0.79±0.12	0.85±0.09	0.70±0.18
Training with high force	Accuracy	KNN	99.23±0.96	96.27±2.55	93.44±2.87	91.02±4.44	89.06±6.11
		SVM	98.79±1.61	96.05±2.45	92.94±3.41	92.51±3.86	89.13±6.10
		LDA	98.36±1.78	96.12±2.69	92.57±2.79	93.90±3.77	89.87±5.73
	Sensitivity	KNN	97.69±2.89	88.81±7.66	80.32±8.61	73.06±13.31	67.17±18.32
		SVM	96.36±4.83	88.16±7.34	78.81±10.22	77.52±11.59	67.38±18.31
		LDA	95.09±5.34	88.37±8.06	77.71±8.38	81.71±11.32	69.61±17.18
	Specificity	KNN	99.54±0.58	97.76±1.53	96.06±1.72	94.61±2.66	93.43±3.66
		SVM	99.27±0.97	97.63±1.47	95.76±2.04	95.50±2.32	93.48±3.66
		LDA	99.02±1.07	97.67±1.61	95.54±1.68	96.34±2.26	93.92±3.44
	Precision	KNN	97.86±2.63	89.90±6.84	82.42±7.76	75.04±13.15	69.53±18.09
		SVM	96.78±4.22	89.57±6.63	81.02±9.60	78.23±12.47	70.30±18.13
		LDA	95.73±4.52	89.71±7.35	80.26±7.69	83.01±10.71	72.20±17.21
	F1 Score	KNN	97.66±2.94	88.55±7.91	79.43±9.10	72.91±13.55	66.32±18.63
		SVM	96.26±4.99	87.92±7.55	77.88±10.5	76.06±13.07	65.96±19.0
		LDA	94.95±5.55	88.25±8.14	76.98±8.62	81.39±11.55	68.72±17.77
	MCC	KNN	0.97±0.03	0.87±0.09	0.77±0.10	0.68±0.16	0.60±0.20
		SVM	0.95±0.06	0.86±0.09	0.75±0.12	0.73±0.15	0.60±0.20
		LDA	0.93±0.07	0.87±0.09	0.74±0.10	0.78±0.13	0.62±0.20

TABLE 1. *(Continued.)* **The EMG-PR performances of different feature selection methods when the classifiers are trained for O3 with one force level and tested for trained orientation with all force levels.**

	Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Training with low force	Accuracy	KNN	97.60±2.28	92.63±4.19	91.06±3.22	89.68±2.81	88.26±5.45
		SVM	97.49±2.36	92.79±3.92	91.06±2.99	90.77±3.43	87.87±5.63
		LDA	96.20±2.31	92.01±3.78	91.44±3.11	92.46±2.60	89.12±4.40
	Sensitivity	KNN	92.81±6.83	77.88±12.58	73.17±9.65	69.04±8.42	64.78±16.36
		SVM	92.46±7.07	78.36±11.77	73.17±8.97	72.32±10.3	63.62±16.89
		LDA	88.61±6.93	76.03±11.34	74.32±9.34	77.39±7.80	67.36±13.21
	Specificity	KNN	98.56±1.37	95.58±2.52	94.63±1.93	93.81±1.68	92.96±3.27
		SVM	98.49±1.41	95.67±2.35	94.63±1.79	94.46±2.06	92.72±3.38
		LDA	97.72±1.39	95.21±2.27	94.86±1.87	95.48±1.56	93.47±2.64
	Precision	KNN	93.39±5.86	82.49±9.60	77.37±7.08	72.67±7.87	70.68±13.9
		SVM	93.30±5.53	83.32±8.42	77.62±7.19	76.79±9.26	69.02±15.03
		LDA	90.03±5.76	80.01±11.45	78.38±8.12	81.11±7.71	72.17±11.92
	F1 Score	KNN	92.62±7.19	77.47±12.52	72.64±9.44	68.41±8.42	64.07±16.34
		SVM	92.36±7.19	77.70±11.92	72.68±8.82	71.6±10.48	62.12±17.74
		LDA	88.23±7.22	75.12±11.88	73.99±9.29	76.86±7.96	66.13±13.76
	MCC	KNN	0.92±0.08	0.75±0.14	0.69±0.11	0.64±0.10	0.63±0.18
		SVM	0.90±0.09	0.76±0.13	0.69±0.10	0.68±0.12	0.61±0.18
		LDA	0.85±0.08	0.72±0.14	0.71±0.11	0.74±0.09	0.63±0.17
Training with medium force	Accuracy	KNN	98.35±1.37	94.29±3.14	93.66±1.86	91.59±3.23	90.62±4.59
		SVM	98.27±1.41	94.35±3.14	94.07±1.91	92.86±2.93	90.70±4.61
		LDA	97.72±1.80	94.28±3.75	93.64±2.12	93.52±3.03	91.88±3.73
	Sensitivity	KNN	95.06±4.12	82.87±9.43	80.97±5.57	74.78±9.70	71.85±13.76
		SVM	94.82±4.24	83.05±9.43	82.22±5.74	78.59±8.78	72.11±13.83
		LDA	93.16±5.40	82.83±11.26	80.93±6.35	80.55±9.09	75.64±11.2
	Specificity	KNN	99.01±0.82	96.57±1.89	96.19±1.11	94.96±1.94	94.37±2.75
		SVM	98.96±0.85	96.61±1.89	96.44±1.15	95.72±1.76	94.42±2.77
		LDA	98.63±1.08	96.57±2.25	96.19±1.27	96.11±1.82	95.13±2.24
	Precision	KNN	95.48±3.54	84.44±8.49	83.08±5.14	75.53±10.13	74.6±13.71
		SVM	95.42±3.42	85.51±7.31	84.54±5.08	79.74±9.21	75.23±13.64
		LDA	94.04±4.35	85.14±9.29	83.50±5.52	81.84±9.13	78.08±10.56
	F1 Score	KNN	95.05±4.10	82.84±9.43	80.49±5.99	74.30±9.87	71.44±13.98
		SVM	94.81±4.18	83.07±9.36	81.74±6.03	77.52±9.46	71.46±14.43
		LDA	93.15±5.28	82.75±11.22	80.46±6.68	80.15±9.47	75.17±11.39
	MCC	KNN	0.94±0.05	0.80±0.11	0.78±0.07	0.70±0.12	0.71±0.15
		SVM	0.93±0.05	0.81±0.10	0.79±0.07	0.74±0.11	0.71±0.14
		LDA	0.91±0.06	0.80±0.13	0.78±0.07	0.77±0.11	0.73±0.14
Training with high force	Accuracy	KNN	98.46±1.07	93.48±2.69	92.99±1.90	91.46±4.10	91.15±4.69
		SVM	97.79±1.44	93.64±2.52	92.90±2.03	92.74±3.94	91.19±4.94
		LDA	96.66±1.94	93.97±2.5	93.01±2.74	93.26±3.34	91.99±4.37
	Sensitivity	KNN	95.37±3.22	80.44±8.06	78.97±5.69	74.39±12.3	73.44±14.08
		SVM	93.37±4.33	80.92±7.56	78.70±6.10	78.23±11.82	73.57±14.81
		LDA	89.98±5.83	81.92±7.51	79.02±8.22	79.77±10.02	75.96±13.12
	Specificity	KNN	99.07±0.64	96.09±1.61	95.79±1.14	94.88±2.46	94.69±2.82
		SVM	98.67±0.87	96.18±1.51	95.74±1.22	95.65±2.36	94.71±2.96
		LDA	98.00±1.17	96.38±1.50	95.80±1.64	95.95±2.00	95.19±2.62
	Precision	KNN	95.81±2.93	84.04±6.74	81.62±6.07	76.40±11.56	76.64±13.93
		SVM	94.07±3.74	83.56±6.69	81.39±5.87	80.55±10.37	77.26±14.06
		LDA	91.55±4.79	84.60±6.57	82.14±7.62	81.91±9.42	79.24±12.41
	F1 Score	KNN	95.33±3.24	80.48±8.04	78.49±5.80	74.37±12.1	73.13±14.3
		SVM	93.28±4.41	80.78±7.68	78.24±6.09	77.83±11.67	73.08±15.45
		LDA	89.90±5.85	81.74±7.80	78.69±8.26	79.33±9.86	75.54±13.52
	MCC	KNN	0.95±0.04	0.78±0.09	0.76±0.07	0.70±0.14	0.71±0.18
		SVM	0.91±0.06	0.78±0.09	0.75±0.07	0.75±0.14	0.70±0.18
		LDA	0.86±0.07	0.79±0.09	0.76±0.10	0.76±0.12	0.72±0.15

to addressing multiple challenging factors, several pieces of research are found on muscle force variation. Recently, Islam *et al.* [15] proposed a non-linear scaling-based feature extraction method to resolve the muscle force variation of transradial amputees employing 84-dimensional feature space. Again, Islam *et al.* [14] extended their previous work and introduced a novel signal normalization scheme to overlap the extracted features of different muscle force levels.

TABLE 2. **The EMG-PR performances of different feature selection methods when the classifiers are trained for one orientation with a medium force level and tested for all orientations with all force levels.**

	Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Training with O1	Accuracy	KNN	92.58±2.73	87.82±3.15	80.09±2.40	82.40±3.73	85.15±4.05
		SVM	92.05±2.80	87.84±3.09	78.51±1.37	82.47±3.71	84.81±4.21
		LDA	91.46±2.93	88.34±3.03	79.96±1.99	81.87±3.52	85.08±3.69
	Sensitivity	KNN	77.73±8.19	63.47±9.45	40.27±7.21	47.20±11.19	55.45±12.14
		SVM	76.15±8.41	63.52±9.28	35.52±4.11	47.40±11.14	54.42±12.62
		LDA	74.38±8.79	65.01±9.10	39.87±5.98	45.61±10.56	55.25±11.08
	Specificity	KNN	95.55±1.64	92.69±1.89	88.05±1.44	89.44±2.24	91.09±2.43
		SVM	95.23±1.68	92.70±1.86	87.10±0.82	89.48±2.23	90.88±2.52
		LDA	94.88±1.76	93.00±1.82	87.97±1.20	89.12±2.11	91.05±2.22
	Precision	KNN	79.76±8.19	68.54±8.82	55.99±8.63	61.35±10.24	60.86±12.2
		SVM	78.47±8.58	69.39±8.37	69.01±10.56	63.26±9.56	61.9±12.25
		LDA	76.54±8.19	69.76±9.03	55.83±8.56	63.20±7.73	61.65±9.15
	F1 Score	KNN	77.43±8.58	62.56±9.61	39.92±6.68	47.12±11.46	54.53±12.18
		SVM	75.47±9.11	62.54±9.55	35.52±3.91	46.71±11.77	53.33±12.14
		LDA	74.15±8.63	64.33±9.24	39.78±5.74	45.29±11.01	54.59±11.47
	MCC	KNN	0.74±0.09	0.58±0.11	0.34±0.08	0.4±0.12	0.47±0.15
		SVM	0.70±0.11	0.58±0.11	0.34±0.05	0.42±0.12	0.47±0.13
		LDA	0.68±0.11	0.59±0.11	0.34±0.05	0.41±0.10	0.47±0.12
Training with O2	Accuracy	KNN	92.84±2.66	88.56±2.78	79.55±2.11	81.51±4.14	86.54±4.15
		SVM	92.37±2.54	88.45±2.81	77.98±1.17	81.04±4.77	85.78±4.37
		LDA	91.58±2.73	88.89±2.26	79.00±1.86	82.76±4.99	86.50±4.34
	Sensitivity	KNN	78.52±7.97	65.67±8.34	38.66±6.33	44.53±12.42	59.62±12.46
		SVM	77.12±7.61	65.34±8.44	33.95±3.50	43.12±14.30	57.33±13.10
		LDA	74.75±8.18	66.67±6.77	37.01±5.58	48.28±14.98	59.51±13.02
	Specificity	KNN	95.7±1.59	93.13±1.67	87.73±1.27	88.91±2.48	91.92±2.49
		SVM	95.42±1.52	93.07±1.69	86.79±0.7	88.62±2.86	91.47±2.62
		LDA	94.95±1.64	93.33±1.35	87.4±1.12	89.66±3.00	91.90±2.60
	Precision	KNN	80.35±7.72	69.36±9.77	77.36±6.39	68.47±8.50	66.45±12.66
		SVM	78.72±7.26	69.00±9.19	79.06±11.08	71.85±11.67	65.13±13.15
		LDA	77.54±7.92	69.92±8.43	73.66±10.71	76.39±9.93	68.31±12.83
	F1 Score	KNN	78.44±8.03	64.52±9.00	37.28±4.72	42.94±12.65	58.9±13.06
		SVM	76.84±7.76	64.03±9.21	33.80±3.41	42.62±13.93	56.49±13.56
		LDA	74.61±8.33	65.86±7.66	36.03±5.03	47.15±14.89	59.28±13.4
	MCC	KNN	0.75±0.10	0.60±0.10	0.39±0.04	0.39±0.09	0.51±0.14
		SVM	0.72±0.09	0.59±0.11	0.36±0.06	0.40±0.10	0.51±0.15
		LDA	0.68±0.10	0.6±0.08	0.37±0.07	0.44±0.11	0.53±0.14
Training with O3	Accuracy	KNN	91.90±2.50	86.93±2.90	80.83±2.54	82.64±2.96	84.08±5.00
		SVM	91.01±2.65	86.38±2.68	79.30±1.61	81.71±2.84	84.21±4.95
		LDA	90.39±3.44	87.32±3.11	80.00±3.40	82.35±2.27	84.82±5.34
	Sensitivity	KNN	75.71±7.49	60.80±8.71	42.48±7.61	47.93±8.87	52.25±15.01
		SVM	73.04±7.96	59.15±8.05	37.91±4.83	45.13±8.51	52.64±14.86
		LDA	71.18±10.33	61.95±9.32	39.99±10.19	47.05±6.80	54.47±16.01
	Specificity	KNN	95.14±1.50	92.16±1.74	88.50±1.52	89.59±1.77	90.45±3.00
		SVM	94.61±1.59	91.83±1.61	87.58±0.97	89.03±1.70	90.53±2.97
		LDA	94.24±2.07	92.39±1.86	88.00±2.04	89.41±1.36	90.89±3.20
	Precision	KNN	79.63±4.98	63.60±8.70	61.33±11.41	59.73±8.04	58.82±14.03
		SVM	77.80±4.51	63.75±6.53	71.23±9.28	62.12±9.61	60.13±14.91
		LDA	76.03±6.48	65.66±8.56	65.28±6.74	63.45±9.69	60.43±14.53
	F1 Score	KNN	75.25±8.13	59.23±9.45	42.45±7.29	47.59±8.89	51.18±14.08
		SVM	72.57±8.32	57.40±8.80	37.37±5.07	44.22±8.44	51.01±14.59
		LDA	70.86±10.12	60.61±9.62	39.98±9.43	46.77±6.91	53.40±15.56
	MCC	KNN	0.71±0.08	0.53±0.11	0.37±0.07	0.40±0.07	0.41±0.17
		SVM	0.68±0.08	0.52±0.10	0.36±0.05	0.39±0.06	0.40±0.17
		LDA	0.64±0.11	0.56±0.10	0.36±0.10	0.41±0.05	0.42±0.18

TABLE 3. The EMG-PR performances of different feature selection methods when the classifiers are trained for two orientations with a medium force level and tested with all orientations with all force levels.

	Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Training with O1 and O2	Accuracy	KNN	95.56±2.51	91.59±2.05	88.82±2.31	88.34±4.12	89.74±3.31
		SVM	95.13±2.60	91.43±2.15	88.72±2.62	89.23±4.05	89.80±3.49
		LDA	93.60±2.63	91.49±2.60	86.35±2.76	89.12±4.52	89.92±4.71
	Sensitivity	KNN	86.68±7.52	74.78±6.16	66.47±6.94	65.01±12.35	69.23±9.92
		SVM	85.38±7.81	74.27±6.44	66.15±7.86	67.69±12.14	69.41±10.47
		LDA	80.79±7.89	74.46±7.79	59.06±8.27	67.36±13.57	69.77±14.14
	Specificity	KNN	97.34±1.50	94.96±1.23	93.29±1.39	93.00±2.47	93.85±1.98
		SVM	97.08±1.56	94.85±1.29	93.23±1.57	93.54±2.43	93.88±2.09
		LDA	96.16±1.58	94.89±1.56	91.81±1.65	93.47±2.71	93.95±2.83
	Precision	KNN	88.5±5.76	78.83±6.81	73.54±6.64	67.2±12.33	72.79±11.31
		SVM	87.34±6.32	78.7±7.73	76.07±7.93	70.4±11.85	73.97±12.21
		LDA	83.62±6.31	77.91±8.81	72.88±7.52	70.24±14.34	72.04±15.08
	F1 Score	KNN	86.61±7.46	74.88±5.96	66.91±6.63	64.77±12.58	69.22±9.88
		SVM	85.21±7.92	74.37±6.38	67.06±7.48	66.71±12.73	69.28±10.66
		LDA	80.86±7.69	74.43±7.96	60.26±8.30	67.16±13.90	69.35±14.45
	MCC	KNN	0.85±0.08	0.71±0.07	0.62±0.08	0.59±0.15	0.68±0.06
		SVM	0.82±0.09	0.71±0.08	0.63±0.08	0.62±0.15	0.69±0.08
		LDA	0.75±0.11	0.71±0.1	0.56±0.09	0.62±0.17	0.66±0.10
Training with O1 and O3	Accuracy	KNN	97.19±2.34	93.37±2.09	88.34±2.58	91.36±4.09	90.69±6.13
		SVM	96.90±2.68	93.34±2.11	87.22±1.91	92.57±3.56	90.98±6.11
		LDA	95.29±2.50	93.63±2.73	87.70±2.45	91.13±4.46	90.79±5.46
	Sensitivity	KNN	91.57±7.01	80.12±6.26	65.02±7.74	74.07±12.26	72.07±18.38
		SVM	90.70±8.05	80.02±6.32	61.66±5.73	77.7±10.68	72.95±18.32
		LDA	85.86±7.51	80.90±8.18	63.09±7.36	73.4±13.39	72.37±16.37
	Specificity	KNN	98.31±1.40	96.02±1.25	93.00±1.55	94.81±2.45	94.41±3.68
		SVM	98.14±1.61	96.00±1.26	92.33±1.15	95.54±2.14	94.59±3.66
		LDA	97.17±1.50	96.18±1.64	92.62±1.47	94.68±2.68	94.48±3.27
	Precision	KNN	92.14±6.40	82.28±5.87	80.89±5.70	75.50±11.37	73.40±18.78
		SVM	92.34±5.82	82.46±5.68	85.38±3.82	79.05±10.21	74.50±18.67
		LDA	86.64±6.90	82.08±7.76	77.87±6.23	74.92±13.28	73.39±16.84
	F1 Score	KNN	91.46±7.16	80.03±6.22	66.64±6.04	73.97±12.29	71.87±18.45
		SVM	90.71±7.92	79.96±6.21	64.84±3.96	77.45±10.91	72.65±18.64
		LDA	85.71±7.55	80.82±8.02	64.42±6.40	73.11±13.75	72.08±16.66
	MCC	KNN	0.90±0.08	0.77±0.07	0.64±0.07	0.69±0.14	0.64±0.23
		SVM	0.89±0.09	0.77±0.07	0.64±0.04	0.74±0.13	0.65±0.22
		LDA	0.81±0.10	0.77±0.10	0.62±0.07	0.69±0.16	0.65±0.20
Training with O2 and O3	Accuracy	KNN	95.73±2.50	92.75±2.23	89.51±2.86	88.02±3.60	91.50±3.19
		SVM	95.49±2.63	92.73±2.64	89.18±3.35	89.00±3.62	91.34±3.54
		LDA	94.13±2.90	91.75±3.36	86.97±2.94	88.11±3.88	90.80±3.79
	Sensitivity	KNN	87.18±7.50	78.26±6.69	68.52±8.57	64.05±10.79	74.50±9.58
		SVM	86.48±7.88	78.20±7.91	67.55±10.06	66.99±10.85	74.02±10.61
		LDA	82.40±8.69	75.25±10.08	60.91±8.82	64.32±11.64	72.4±11.38
	Specificity	KNN	97.44±1.50	95.65±1.34	93.70±1.71	92.81±2.16	94.90±1.92
		SVM	97.29±1.58	95.64±1.58	93.51±2.01	93.40±2.17	94.80±2.12
		LDA	96.48±1.74	95.05±2.02	92.18±1.76	92.86±2.33	94.48±2.28
	Precision	KNN	89.47±4.41	80.92±5.83	73.87±6.80	66.4±10.32	77.39±8.72
		SVM	88.76±4.97	81.33±6.32	73.92±7.80	69.78±9.91	76.80±9.70
		LDA	84.94±5.62	77.68±8.23	72.13±11.8	66.74±11.54	73.52±11.25
	F1 Score	KNN	87.15±7.37	78.09±6.42	68.66±8.28	64.09±10.60	74.23±9.55
		SVM	86.35±7.85	78.11±7.45	68.01±9.61	66.52±11.01	73.62±10.49
		LDA	82.16±8.96	74.99±9.91	61.42±9.39	63.87±11.86	71.88±11.82
	MCC	KNN	0.85±0.08	0.75±0.08	0.64±0.09	0.58±0.13	0.69±0.10
		SVM	0.83±0.09	0.75±0.09	0.64±0.11	0.61±0.13	0.68±0.09
		LDA	0.75±0.13	0.71±0.11	0.57±0.11	0.58±0.14	0.64±0.12

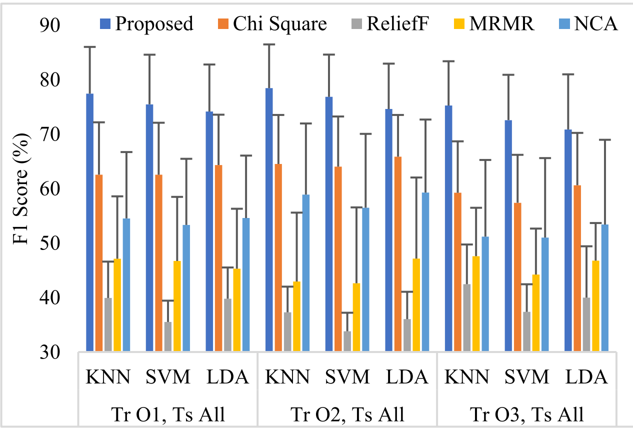


FIGURE 4. **The F1 scores of different feature selection methods when the classifiers are trained for one orientation with a medium force level and tested for all orientations with all force levels.**

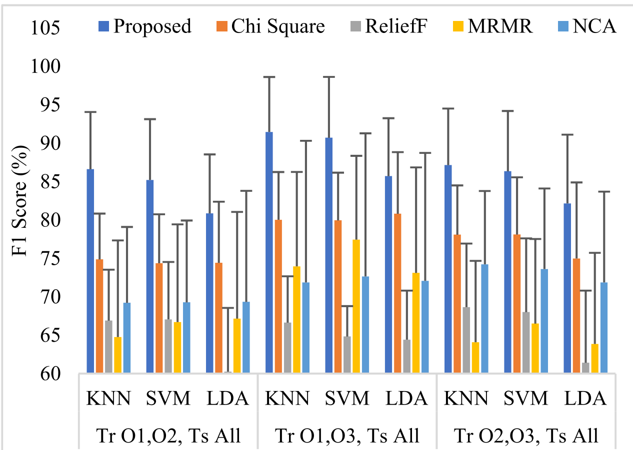


FIGURE 5. **The F1 scores of different feature selection methods when the classifiers are trained for two orientations with a medium force level and tested with all orientations with all force levels.**

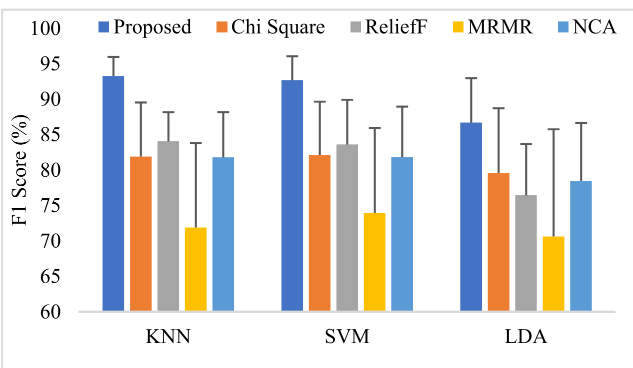


FIGURE 6. **The F1 scores of different feature selection methods when the classifiers are trained for all orientations with a medium force level and tested with all orientations with all force levels.**

In addition to these, Al-Timemy *et al.* [24] proposed a feature extraction method based on orientation between a set of spectral moments descriptors. This work utilized 48-dimensional feature space to resolve muscle force variation. So, most of the recent works propose a unique feature extraction method that can resolve a limiting factor. Also, these works utilize a high dimensional feature space, multiple orientations, and sometimes multiple force levels for training the classifiers. These multiple factors increase training time of classifier, data dimensionality of feature space, design complexity, and computational power of the hardware as well [19]. Finally, it can be mentioned here that, we didn't find any literature studying in identifying important feature to resolve multiple limiting factors.

Algorithm 1 The Proposed Feature Selection Method

1: Initialize $K = I \times J$, total number of features, I number of features from J number of channels
2: Temporary feature array $F = [F_1, F_2, \ldots, F_K]$
3: Proposed Set $S = \{\}$
4: Initialize maximum performance $P_{High} = 0$
5: Initialize counter $i = 1$
6: $S = S \cup F[i]$, set union operation
7: $P[i] = \text{F1 Score}_{KNN}(S)$
8: $S = S - F[i]$, set difference operation
9: $i = i + 1$
10: if $i <= K$ GO TO step 6
11: $P_{Max} = P[1]$, j=2
12: IF $P[j] > P_{Max}$ THEN
  BEGIN
    $P_{Max} = P[j]$
    $MaxID = j$
  END
13: $j = j + 1$
14: IF $j <= K$ GO TO step 12
15: IF $P_{Max} < P_{High}$
  THEN GO TO step 21
16: $S = S \cup F[MaxID]$, set union operation
17: $P_{High} = P_{Max}$
18: $F[MaxID] = F[k]$
19: IF $k > 1$
  THEN $k = k - 1$
  ELSE GO TO step 21
20: GO TO step 5
21: END

There are mainly two methods in EMG feature selection, including filter-based and wrapper-based methods. The filter-based method includes chi-square [25], ReliefF [26], minimum redundancy maximum relevance (MRMR) [27], and neighborhood component analysis (NCA) [26] which are relatively faster, scalable, and independent of the classification algorithm. However, their performance is not high compared to the wrapper-based method [28]. Popular wrapper-based method includes sequential forward selection [29], [30], genetic algorithms [31], ant colony optimization [31] and particle swarm optimization [32]. Among these, the sequential forward selection is a classical and reliable method used widely for EMG channel selection [33]–[35] or EMG feature

TABLE 4. The EMG-PR performances of different feature selection methods when the classifiers are trained for all orientations with a medium force level and tested with all orientations and all force levels.

Parameter	Classifier	Proposed	Chi-Square	ReliefF	MRMR	NCA
Accuracy	KNN	97.77±0.89	93.97±2.52	94.72±1.36	90.61±4.03	93.93±2.15
	SVM	97.59±1.11	94.07±2.48	94.59±2.08	91.48±3.85	94.01±2.33
	LDA	95.56±2.10	93.27±2.94	92.20±2.40	90.30±4.81	92.88±2.64
Sensitivity	KNN	93.31±2.66	81.91±7.56	84.17±4.08	71.84±12.10	81.80±6.45
	SVM	92.76±3.33	82.21±7.43	83.76±6.24	74.44±11.56	82.02±6.98
	LDA	86.67±6.30	79.80±8.81	76.60±7.19	70.90±14.43	78.64±7.91
Specificity	KNN	98.66±0.53	96.38±1.51	96.83±0.82	94.37±2.42	96.36±1.29
	SVM	98.55±0.67	96.44±1.49	96.75±1.25	94.89±2.31	96.40±1.40
	LDA	97.33±1.26	95.96±1.76	95.32±1.44	94.18±2.89	95.73±1.58
Precision	KNN	93.53±2.60	83.02±7.54	84.86±4.15	72.79±11.53	82.80±6.50
	SVM	93.00±3.18	83.26±7.46	84.38±6.17	74.53±11.86	82.94±7.04
	LDA	87.40±5.83	80.53±9.00	76.91±7.22	71.42±15.14	79.09±8.24
F1 Score	KNN	93.27±2.71	81.91±7.63	84.05±4.13	71.90±11.94	81.79±6.40
	SVM	92.69±3.38	82.15±7.51	83.61±6.32	73.94±12.03	81.85±7.12
	LDA	86.70±6.28	79.58±9.14	76.44±7.25	70.64±15.12	78.47±8.21
MCC	KNN	0.92±0.03	0.79±0.09	0.81±0.05	0.67±0.14	0.79±0.08
	SVM	0.91±0.04	0.79±0.09	0.81±0.07	0.69±0.14	0.79±0.08
	LDA	0.81±0.09	0.76±0.11	0.72±0.09	0.65±0.18	0.74±0.10

selection [36], [37]. Nevertheless, the method increases the dimension of feature space by the total number of features or the number of channels.

This study has proposed a feature selection method to resolve forearm orientation and muscle force variation simultaneously. In this proposed method, we considered 162-dimensional feature space generated by employing [14], [30] as described in Section II-B. In this proposed algorithm, the feature extracted from each EMG channel was considered a unique feature rather than computing a feature across all channels as done in a traditional sequential forward selection algorithm. So, the proposed method considered $K = I \times J$ number of unique features for an I number of features extracted from J number of EMG channels. Finally, the proposed feature selection method selected those features only which contributed to the EMG-PR performance. Thus, the proposed feature selection method selects a specific feature from a specific channel rather than selecting either feature [36], [37] or channel [33]–[35]. In addition, our proposed algorithm increases the dimension of features by one, whereas the sequential forward selection algorithm increases the dimension by its total number of channels. Thus, the dimension of selected features through the proposed feature selection algorithm is always less than the dimension of features obtained by the sequential forward selection algorithm.

Consequently, the proposed feature selection method could reduce the training time of the classifier, data dimensionality of feature space, design complexity, and computational power of the hardware. In addition to a reduced number of features, the selected features indicate the importance of a channel and a feature to resolve the limiting factors. In this research, we also considered four existing feature selection methods to compare and validate the EMG-PR performance of the proposed feature selection method. The experimental data showed that the proposed feature selection method significantly improved the accuracy, sensitivity, specificity, precision, F1 score, and MCC by 3.18% to 4.28%, 9.14% to 12.85%, 1.83% to 2.57%, 8.30% to 10.99%, 9.22% to 13.92%, and 0.11 to 0.15, respectively when the proposed method was compared second-best performing feature selection method (Section III). In this study, the proposed feature selection method achieved a forearm orientation and muscle force invariant F1 score of 91.46% for training KNN classifier with orientations O1 and O3 with a medium force level. The achieved performance was much higher than the existing two works that employed three orientations for training. Also, we trained the KNN classifier for all orientations with medium force level, and then we achieved an F1 score of 93.27%, which was improved by 2.27% to 2.92% (Table 5). In addition to improved EMG-PR performances, the proposed feature selection method selected the least number of features of 7 to 20 (Table 28 and Table 30), which was less than the feature space used in the existing works. So, the proposed feature selection method would be a promising method to resolve both forearm orientation and muscle force variation by employing efficient features only. However, in this work, we have employed three classifiers, i.e., KNNs, support vector machines (SVMs), and linear discriminant analysis (LDAs), to estimate and validate the EMG-PR performance. These classifiers are utilized as they require a low computational cost and achieve a reasonable EMG-PR performance [14]. Also, the achieved EMG-PR performances for each feature selection method were validated statistically by utilizing a two-way analysis of variance (ANOVA),

TABLE 5. The comparison of EMG-PR performance with existing works.

Reference	Dynamic Factor	EMG Dataset			Method				Performance (%)
		Subject	Channel	Movement	Feature set	Dimension	Condition	Classifier	
He *et al.* [16]	3 muscle force levels	9-healthy	8	9	Global normalized six frequency band energy	48	Training for 50% force level	LDA	91
Al-Timemy *et al.* [24]	3 muscle force levels	9-amputees	8	6	Six-time domain power spectral descriptors	48	Training for all force levels	LDA	92
Islam *et al.* [14]	3 muscle force levels	9-amputees	8	6	Signal normalized seven non-linear features with correlation coefficients	84	Training for all force levels	LDA SVM	92
Khushaba *et al.* [20]	3 forearm orientations and 3 muscle force levels	10-healthy	6 and 3-D accelerometer	6	Six-time domain power spectral descriptors and accelerometer features	39	Training for all orientations with a medium force level	SVM	91
Rajapriya *et al.* [19]	3 forearm orientations and 3 muscle force levels	10-healthy	6	6	Wavelet bispectrum based 16 features	96	Training for all orientations with a medium force level	SVM	90.35
This work	3 forearm orientations and 3 muscle force levels	10-healthy	6 and 3-D accelerometer	6	Signal normalized nine non-linear features, correlation coefficients, 15 order AR coefficients, and accelerometer features	7 to 19	Training for all orientations with a medium force level	KNN	93.27
						7 to 20	Training for O1 and O3 with a medium force level	KNN	91.46

considering the classifier and feature selection method as independent parameters.

The remaining paper is arranged as follows. Section II describes the proposed feature selection method, the EMG datasets for three orientations with three force levels, feature extraction, and classification. Section III presents the impact of the number of features and the feature selection methods on the EMG-PR performance, the EMG-PR performances for different training and testing cases, and the comparison of the achieved performances with existing works. Section IV investigates the details behind the improved forearm orientation and muscle force invariant EMG-PR performance, and finally, Section V concludes with the overall experimental results.

TABLE 6. Summary of two-way ANOVA when classifiers are trained with O2 with one force level and tested with trained orientation with all force levels.

Independent variable	p-value
Classifier	0.680
Feature selection	p<<0.001
Classifier*Feature selection	0.570

TABLE 7. Comparison between the feature selection methods when classifiers are trained with O2 with one force level and tested with trained orientation with all force levels.

Feature selection method		p-value
Chi-Square	MRMR	p<<0.001
	NCA	p<<0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
MRMR	Chi-Square	p<<0.001
	NCA	p<<0.001
	Proposed	p<<0.001
	ReliefF	1.000
NCA	Chi-Square	p<<0.001
	MRMR	p<<0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
Proposed	Chi-Square	p<<0.001
	MRMR	p<<0.001
	NCA	p<<0.001
	ReliefF	p<<0.001
ReliefF	Chi-Square	p<<0.001
	MRMR	1.000
	NCA	p<<0.001
	Proposed	p<<0.001

TABLE 8. Summary of two-way ANOVA when classifiers are trained with one orientation with a medium force level and tested with all orientations with all force levels.

Independent variable	p-value
Classifier	0.260
Feature selection	p<<0.001
Classifier*Feature selection	0.800

TABLE 9. Comparison between the feature selection methods when classifiers are trained with one orientation with a medium force level and tested with all orientations with all force levels.

Feature selection method		p-value
Chi-Square	MRMR	p<<0.001
	NCA	p<<0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
MRMR	Chi-Square	p<<0.001
	NCA	p<<0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
NCA	Chi-Square	p<<0.001
	MRMR	p<<0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
Proposed	Chi-Square	p<<0.001
	MRMR	p<<0.001
	NCA	p<<0.001
	ReliefF	p<<0.001
ReliefF	Chi-Square	p<<0.001
	MRMR	p<<0.001
	NCA	p<<0.001
	Proposed	p<<0.001

II. METHODOLOGY

A. THE PROPOSED FEATURE SELECTION METHOD

In particular, in EMG-PR, a large number of features have been proposed over the decades, and these features are problem-specific [14], [24], [38], [39]. Therefore, to resolve any EMG-PR problem, an efficient feature selection method is necessary to find the least number of features and achieve the highest pattern recognition performance with low computational power [27].

As shown in Algorithm 1, we evaluated the I number of features from the J number of EMG channels in this proposed method. Thus, the total number of features K is equal to $I \times J$. We considered each of the K features as

TABLE 10. Summary of two-way ANOVA when classifiers are trained with two orientations with a medium force level and tested with all orientations with all force levels.

Independent variable	p-value
Classifier	0.051
Feature selection	p<<0.001
Classifier*Feature selection	0.723

TABLE 11. Comparison between the feature selection methods when classifiers are trained with two orientations with a medium force level and tested with all orientations with all force levels.

Feature selection method		p-value
Chi-Square	MRMR	p<<0.001
	NCA	0.002
	Proposed	p<<0.001
	ReliefF	p<<0.001
MRMR	Chi-Square	p<<0.001
	NCA	0.516
	Proposed	p<<0.001
	ReliefF	0.311
NCA	Chi-Square	0.002
	MRMR	0.516
	Proposed	p<<0.001
	ReliefF	p<<0.001
Proposed	Chi-Square	p<<0.001
	MRMR	p<<0.001
	NCA	p<<0.001
	ReliefF	p<<0.001
ReliefF	Chi-Square	p<<0.001
	MRMR	0.311
	NCA	p<<0.001
	Proposed	p<<0.001

TABLE 12. Summary of two-way ANOVA when classifiers are trained with all orientations with a medium force level and tested with all orientations with all force levels.

Independent variable	p-value
Classifier	0.012
Feature selection	p<<0.001
Classifier*Feature selection	0.960

TABLE 13. Comparison between the classifiers when classifiers are trained with all orientations with a medium force level and tested with all orientations with all force levels.

Classifier		p-value
KNN	LDA	0.037
	SVM	1.000
LDA	KNN	0.037
	SVM	0.024
SVM	KNN	1.000
	LDA	0.024

TABLE 14. Comparison between the feature selection methods when classifiers are trained with all orientations with a medium force level and tested with all orientations with all force levels.

Feature selection method		p-value
Chi-Square	MRMR	p<<0.001
	NCA	1.000
	Proposed	p<<0.001
	ReliefF	1.000
MRMR	Chi-Square	p<<0.001
	NCA	0.001
	Proposed	p<<0.001
	ReliefF	p<<0.001
NCA	Chi-Square	1.000
	MRMR	0.001
	Proposed	p<<0.001
	ReliefF	1.000
Proposed	Chi-Square	p<<0.001
	MRMR	p<<0.001
	NCA	p<<0.001
	ReliefF	p<<0.001
ReliefF	Chi-Square	1.000
	MRMR	p<<0.001
	NCA	1.000
	Proposed	p<<0.001

a unique feature. The reason is that each feature increases the total number of features by the total number of channels since each feature is evaluated across all EMG channels. Also, the extracted features from all EMG channels do not contribute to enhancing the EMG-PR performance [40]. However, the proposed feature selection method selects those features only, which contributes to the F1 score. In this method, the performance was evaluated for each feature, and the best-performing feature was selected. Then, the selected feature was grouped with each of the remaining features, and the group of two features that provided the highest performance was selected. The procedure was continued until the addition of a new feature contributed to the performance.

This study considered the KNN classifier to evaluate the F1 score since the KNN classifier performed better than SVM and LDA (Section III). For performance evaluation with various training and testing datasets, we employed widely used 5-fold cross-validation as described in Section III-D. Therefore, the proposed feature selection method would be able to find the least number of features without compromising the EMG-PR performance.

TABLE 15. Selected features for training classifiers with O1 with a low force level and testing with O1 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	17	C1F2, C1AcF, C5F3, C2AcF, C1F3, C3F9, CC2, CC13, C1AR11, C6AR14, C1AR15, C1F8, C1F5, CC8, C1AR13, C1F7, C3F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4	C1AcF, C2AcF, C3AcF, C1F1, C1F2, CC2, C1F3, C1F7, CC6, C5F1, C5F7, C1F4, C5F3, C5F4, C5F8, C1F8, C4F6	C1AcF, C3F2, CC7, CC3, C6AR15, C1AR15, C2AR15, CC14, CC1, C5AR15, C3AR15, C1F6, C4AR11, CC9, C2F4, C1F1, CC5	C4F2, C4F3, C1F2, C4F4, C1F3, C4F5, C4F6, C1F4, C1F5, C1F6, C2F6, C4F7, C4F8, C2F5, C4F9, C4F1, C2F4
S2	7	C5F3, C1AcF, C1F2, C3F2, C6F6, C5F2, C2F9	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C1AcF, C2AcF, C3AcF, C2F1, CC15, C2F7, C6F2	C1AcF, C5F3, C2AR13, CC7, C6AR15, C1AR14, C5AR15	C4AR7, C2AR6, C5AR7, C3AR10, C3AR9, C5AR6, C3AR5
S3	10	C4F7, C1F2, C3F2, CC15, C2F8, C1F1, CC7, C5AR5, CC10, CC14	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F3, C1F7, C4F3, C1F4, C4F4	C4F3, C2AcF, C2AR8, C3AR14, C5AR15, CC11, CC12, CC15, C4AR15, CC2	C1F3, C1F4, C1F2, C1F5, C1F6, C4F2, C4F3, C4F4, C4F5, C3F2
S4	8	C1AcF, C3F1, C1F1, C2AcF, C5F3, C1F3, C3F3, CC10	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C1AcF, C2AcF, C3AcF, C5F2, C5F1, C5F3, C5F7, C3F1	C1AcF, C4F2, C5AR15, C3AR14, C2AR14, CC8, C4AR15, C5F7	C4F3, C5F3, C4F4, C3F2, C3F3, C5F2, C3F4, C4F5
S5	10	C1F5, C5F7, C6F1, C3F6, C1AcF, C5F9, C1F4, C5F1, C5F2, C5F8	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C5F3, C1F4	C1AcF, C2AcF, C3AcF, C2F1, C2F2, CC6, C2F7, C3F9, C3F8, C5F4	C5F3, C2AcF, C6AR1, C1AR14, C2AR14, C5AR15, CC4, C4AR15, CC14, CC2	C3F6, C3F5, C3F4, C3F3, C3F2, C5F3, C5F4, C1F5, C1F6, C5F5
S6	8	C4F7, C3F8, C2F2, C5F9, C4F3, C2AcF, C1F1, C3F2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C3AcF, C2AcF, C1AcF, C4F1, C6F2, C4F2, C6F1, C3F2	C4F7, C1AcF, C2AR2, C6AR15, C1AR13, C2AR14, C5AR15, C4AR15	C3AR8, C3AR7, C5AR7, C1AR8, C3AR9, C4AR8, C5AR8, C4AR7
S7	6	C4F3, C5F2, CC5, C4F1, C3F6, C4F2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1	C2AcF, C3AcF, C4F1, C6F1, C6F2, C4F2	C4F1, C5AR6, C4AR10, C3AR14, C1AR14, C6AR15	C3F3, C3F2, C3F4, C4F6, C4F5, C4F4
S8	16	C4F7, C3F3, C1F5, C3AcF, CC1, C4AR10, C3F8, C1AcF, C1F1, C2AcF, C3F1, C1F9, C3F2, C3F4, C4F1, C5AR15	C1F1, C2F1, C3F1, C4F1, C1F2, C2F2, C3F2, C4F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4, C3F4	C1AcF, C2AcF, C3AcF, CC11, C3F1, C3F7, C3F2, C3F3, C3F8, C3F4, CC2, C3F9, C3F5, C3F6, CC3, CC1	C1F2, C4AR5, C1AR13, C3AR13, C2AR14, C6AR15, CC12, CC11, C4AR15, C2AcF, CC15, C3F2, CC1, C1F6, C2AR3, C4F8	C4F3, C4F4, C3F3, C4F5, C3F4, C3F2, C3F6, C1F4, C1F5, C3F5, C1F6, C1F3, C2F5, C4F6, C2F6, C4F2
S9	9	C5F3, C2F6, C1F6, C1AcF, C4AR10, C4F3, C5AR9, C3AR15, C5AR2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C1AcF, C4F4, C4F5, C4F3, C4F6, C1F1, C1F2, C4F8, C4F9	C5F9, C1F1, C4AR15, C6AR13, C2AR14, C3AR14, C5AR14, CC12, C4F3	C5F5, C5F4, C5F6, C1F2, C5F3, C1F3, C5F2, C3F4, C3F5
S10	11	C3AcF, C1AcF, C3F4, C4F5, C5F9, C1F1, C3F6, C2AcF, C3F9, C5F6, C1AR2	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C4F3, C5F3, C1F4	C3AcF, C1AcF, C2AcF, C2F1, C1F6, C2F2, C1F5, C2F3, C2F7, C4F5, C2F4	C1AcF, C2F8, C3AR13, CC2, C1AR15, C2AR10, CC15, CC11, C4F4, C3AcF, C6F5	C5AR6, C5AR7, C1F4, C1F3, C1F5, C4F5, C1F6, C4F6, C4F4, C1F2, C4F3

TABLE 16. Selected features for training classifiers with O1 with a medium force level and testing with O1 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	17	C5F3, C1AcF, C1F3, CC9, C3AR11, C1AR1, CC5, CC1, C1F5, C4F9, CC2, C6AR7, C6AR9, C2AR3, C1F1, C1AR7, C1F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4	C1AcF, C2AcF, C3AcF, C1F1, C1F2, CC2, C1F3, C1F7, CC6, C5F1, C5F7, C1F4, C5F3, C5F4, C5F8, C1F8, C4F6	C1AcF, C3F2, CC7, CC3, C6AR15, C1AR15, C2AR15, CC14, CC1, C5AR15, C3AR15, C1F6, C4AR11, CC9, C2F4, C1F1, CC5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3
S2	10	C5F3, C1AcF, C2F8, C3AcF, CC8, C2F6, C4F7, C5F2, C4F1, C2F5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2	C1AcF, C2AcF, C3AcF, C2F1, CC15, C2F7, C6F2, C6F1, CC14, C2F2	C1AcF, C5F3, C2AR13, CC7, C6AR15, C1AR14, C5AR15, C3AR14, C3F2, C1F7	C6AR6, C4AR9, C2AR9, C1AR6, C4AR8, C1AR7, C6AR7, C5AR6, C5AR7, C2AR8
S3	8	C4F7, C1F1, C6F7, C4F1, C1AR6, C2F1, C3F1, C1F3	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F3, C1F7, C4F3	C4F3, C2AcF, C2AR8, C3AR14, C5AR15, CC11, CC12, CC15	C1F2, C1F3, C1F4, C4F2, C4F3, C1F5, C4F4, C1F6
S4	9	C1AcF, C2AcF, C1F2, C5F2, CC1, C1AR12, C3F1, C3AcF, C4AR14	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C1AcF, C2AcF, C3AcF, C5F2, C5F1, C5F3, C5F7, C3F1, C3F7	C1AcF, C4F2, C5AR15, C3AR14, C2AR14, CC8, C4AR15, C5F7, C3F1	C5AR8, C6AR9, C5AR9, C6AR10, C3AR8, C5AR10, C2AR6, C2AR9, C4AR9
S5	13	C1F5, C5F1, C3F5, C1AcF, C6F1, C5F8, CC15, C3AcF, CC10, C1F4, C5F3, C3AR14, C3F9	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C5F3, C1F4, C3F4, C5F4, C1F5	C1AcF, C2AcF, C3AcF, C2F1, C2F2, CC6, C2F7, C3F9, C3F8, C5F4, C3F5, C3F6, C5F8	C5F3, C2AcF, C6AR1, C1AR14, C2AR14, C5AR15, CC4, C4AR15, CC14, CC2, CC9, C3F1, C1AcF	C2AR10, C2AR9, C1F5, C1F4, C3F5, C1F6, C3F6, C3F4, C1F3, C3F3, C2AR11, C1F2, C3F2
S6	11	C4F7, C1F2, C1AcF, C2AcF, C6F1, C3F3, C5F5, C6F9, C5F6, C4F5, C6F3	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2	C3AcF, C2AcF, C1AcF, C4F1, C6F2, C4F2, C6F1, C3F2, C3F3, C3F1, C3F4	C4F7, C1AcF, C2AR2, C6AR15, C1AR13, C2AR14, C5AR15, C4AR15, C3AR13, CC2, CC5	C2F3, C2F2, C2F4, C3F3, C3F4, C3F6, C3F5, C2F5, C3F2, C2F6, C5F3
S7	11	C4F3, C3F3, C5AR4, C4F1, C5F1, C4F2, C6F1, C4F7, C4F4, C3F5, C4F5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C3F2, C4F2, C5F2, C6F2	C2AcF, C3AcF, C4F1, C6F1, C6F2, C4F2, C2F1, C4F3, C4F7, C2F7, C1AcF	C4F1, C5AR6, C4AR10, C3AR14, C1AR14, C6AR15, C2AR15, CC7, C3AR1, C3AcF, CC5	C4F5, C4F4, C4F6, C4F3, C4F2, C3F3, C3F4, C3F2, C3F5, C3F6, C1F3
S8	7	C4F7, C3F3, C1AcF, C4F2, C4F3, C4F4, C4F5	C1F1, C2F1, C3F1, C4F1, C1F2, C2F2, C3F2	C1AcF, C2AcF, C3AcF, CC11, C3F1, C3F7, C3F2	C1F2, C4AR5, C1AR13, C3AR13, C2AR14, C6AR15, CC12	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2
S9	11	C5F3, C4F7, C1F9, CC1, C3F3, C1F1, CC10, C2F9, C4F8, C5AR8, C3F4	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2	C1AcF, C4F4, C4F5, C4F3, C4F6, C1F1, C1F2, C4F8, C4F9, C4F7, C1F3	C5F9, C1F1, C4AR15, C6AR13, C2AR14, C3AR14, C5AR14, CC12, C4F3, CC4, C2F5	C1F3, C1F2, C1F4, C4F4, C4F5, C4F6, C4F3, C1F5, C1AR6, C1AR5, C1F6
S10	9	C1AcF, C2AcF, C4F5, C4F4, C2F4, C3AcF, C3F6, CC13, C1F2	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C4F3	C3AcF, C1AcF, C2AcF, C2F1, C1F6, C2F2, C1F5, C2F3, C2F7	C1AcF, C2F8, C3AR13, CC2, C1AR15, C2AR10, CC15, CC11, C4F4	C6AR6, C6AR7, C6AR5, C6AR8, C1F4, C1F3, C1F5, C4F5, C4F4

B. DESCRIPTION OF EMG DATASET

In this research, the EMG dataset was collected from Khushaba *et al.* [20] using an online respiratory (https://www.rami-khushaba.com/electromyogram-emg-repository.html, accessed on Oct. 12, 2021). The dataset includes ten intact limbed subjects (S1 to S10) aged between 20 and 33 years. The EMG signal was recorded using the Bagnoli desktop EMG system (Delsys Inc., USA). In this data recording, six equally spaced EMG signal electrodes were attached across the forearm circumference, where their common reference electrode was placed near the wrist. In addition, the EMG signal was digitalized at a 4000 Hz sampling rate using National Instruments, BNC-2090, with 12 bits resolution. During data recording, each subject performed six movements: hand close, hand open, wrist extension, wrist flexion, wrist ulnar deviation, and wrist radial deviation. Each movement was repeated three times (known as trials). In addition to performing complex movements, three forearm orientations (O1, wrist at rest (O2), and O3) as shown in Fig. 1 and three muscle contraction force levels (low, medium, and high) were considered in this recording. Therefore, each subject performed 162 trials (6 movements $\times$ 3 orientations $\times$ 3 muscle force levels $\times$ 3 trials). In this data recording, each trial was performed for 5 s duration with a 10 s rest between any successive trials to minimize the effect of muscle fatigue. In this dataset, an additional 3-D accelerometer (MPU-6050 from InvenSense) was also attached to the wrist of the subject to observe wrist acceleration. The accelerometer data was sampled at 26.6$\pm$0.30 Hz.

TABLE 17. Selected features for training classifiers with O1 with a high force level and testing with O1 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	12	C1AcF, C2F2, C5AR4, C2AcF, C5F3, C1F8, C1F5, C1F1, C3F5, C2F1, C3F8, C2F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3	C1AcF, C2AcF, C3AcF, C1F1, C1F2, CC2, C1F3, C1F7, CC6, C5F1, C5F7, C1F4	C1AcF, C3F2, CC7, CC3, C6AR15, C1AR15, C2AR15, CC14, CC1, C5AR15, C3AR15, C1F6	C5AR9, C4F3, C4F4, C4AR10, C4F5, C4F6, C4F2, C4AR9, C5AR10, C1F2, C5AR8, C1F3
S2	3	C1AcF, C3F7, C5F3	C1F1, C2F1, C3F1	C1AcF, C2AcF, C3AcF	C1AcF, C5F3, C2AR13	C2F3, C2F4, C2F5
S3	19	C1F2, C2F2, C4F7, CC1, C1F1, C3F1, C6F8, CC7, C2F7, CC9, C1AcF, C1F7, C1AR5, C4F9, C2F1, CC14, CC2, C1F3, C1F5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4, C2F4, C3F4	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F3, C1F7, C4F3, C1F4, C4F4, C4F2, C4F1, C1F8, C4F7, CC2, C4F5, C3F1, C3F2, C4F6	C4F3, C2AcF, C2AR8, C3AR14, C5AR15, CC11, CC12, CC15, C4AR15, CC2, C6AR15, C2F1, C3F1, C1AR14, C1F5, C4AR8, CC1, C3F6, CC7	C1F3, C1F2, C1F4, C1F5, C1F6, C4F2, C3F2, C3F3, C2F2, C4F3, C3F4, C1F1, C4F6, C2F6, C4F5, C2F3, C1F7, C4F4, C2F4
S4	9	C5F3, C1AcF, C1F1, C3F1, C2AcF, C5AR1, C3F4, CC8, C3F7	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C1AcF, C2AcF, C3AcF, C5F2, C5F1, C5F3, C5F7, C3F1, C3F7	C1AcF, C4F2, C5AR15, C3AR14, C2AR14, CC8, C4AR15, C5F7, C3F1	C5F3, C5F2, C4AR10, C5F4, C5F5, C5F6, C4F3, C4F4, C3F3
S5	11	C1F9, C5F3, C3F6, CC6, C2AcF, C1F5, C1AcF, C1F3, C1F4, C1F6, C5F7	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C5F3, C1F4, C3F4	C1AcF, C2AcF, C3AcF, C2F1, C2F2, CC6, C2F7, C3F9, C3F8, C5F4, C3F5	C5F3, C2AcF, C6AR1, C1AR14, C2AR14, C5AR15, CC4, C4AR15, CC14, CC2, CC9	C3F5, C3F4, C3F6, C3F3, C5F4, C5F5, C3F2, C5F6, C1F4, C1F5, C5F3
S6	10	C4F8, C4F1, C1F1, C3F1, C2AcF, C1F2, C4F4, C1AcF, C6F3, C4F7	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C3AcF, C2AcF, C1AcF, C4F1, C6F2, C4F2, C6F1, C3F2, C3F3, C3F1	C4F7, C1AcF, C2AR2, C6AR15, C1AR13, C2AR14, C5AR15, C4AR15, C3AR13, CC2	C3AR6, C3AR5, C3F4, C3F3, C3F5, C4F2, C3F6, C4F3, C4F4, C4F5
S7	19	C4F3, C3F4, C5AR2, C6F2, C1F9, C4F1, C3F3, CC5, C4F6, C4F8, C5AR9, C5F1, C1AR4, CC15, CC4, C3F2, CC14, C5F2, C6AR13	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C3F2, C4F2, C5F2, C6F2, C1F3, C3F3, C4F3, C5F3, C6F3, C1F4, C3F4, C4F4	C2AcF, C3AcF, C4F1, C6F1, C6F2, C4F2, C2F1, C4F3, C4F7, C2F7, C1AcF, C4F4, CC1, C4F8, C4F5, C4F9, C2F8, C4F6, C1F1	C4F1, C5AR6, C4AR10, C3AR14, C1AR14, C6AR15, C2AR15, CC7, C3AR1, C3AcF, CC5, C2F8, CC14, C3F5, C6F1, C1AR1, CC11, C5F5, C6AR4	C6AR7, C1AR7, C2AR8, C5AR7, C3AR7, C1AR8, C5AR6, C6AR8, C3AR6, C2AR7, C5AR8, C4F5, C4F4, C4F6, C4F3, C1AR9, C3AR8, C4F2, C2AR6
S8	8	C4F3, C3F3, C2F3, C3F2, C3F1, C3F7, C4F1, C1F9	C1F1, C2F1, C3F1, C4F1, C1F2, C2F2, C3F2, C4F2	C1AcF, C2AcF, C3AcF, CC11, C3F1, C3F7, C3F2, C3F3	C1F2, C4AR5, C1AR13, C3AR13, C2AR14, C6AR15, CC12, CC11	C2AR7, C1AR8, C4AR7, C4AR8, C1AR9, C5AR9, C1AR7, C3AR7
S9	10	C5F2, C1F8, C1AcF, CC1, C3F6, C4F4, C2AcF, C2F1, CC10, C5F4	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C1AcF, C4F4, C4F5, C4F3, C4F6, C1F1, C1F2, C4F8, C4F9, C4F7	C5F9, C1F1, C4AR15, C6AR13, C2AR14, C3AR14, C5AR14, CC12, C4F3, CC4	C6AR8, C5AR8, C1AR5, C6AR9, C2AR6, C5AR7, C3AR7, C4AR6, C2AR7, C1F2
S10	7	C1AcF, C3AcF, C4F5, C3F6, C1F3, C5F6, C2AcF	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3	C3AcF, C1AcF, C2AcF, C2F1, C1F6, C2F2, C1F5	C1AcF, C2F8, C3AR13, CC2, C1AR15, C2AR10, CC15	C2F2, C2F3, C1F4, C4F5, C1F5, C4F6, C4F4

C. FEATURE EXTRACTION

In this research, we extracted nine features (F1 to F9) and correlation coefficients (CCs) according to Islam *et al.* [14]. In this feature extraction method, the multichannel EMG signals were normalized by the root mean square (RMS) value of the current window since the signal normalization scheme is very much helpful to overlap muscle activation patterns of different muscle contraction forces [14]. Then, the features were extracted as follows:

$$F1 = log(\frac{1}{N}\sum_{i=0}^{N-1}|x[i]|) \tag{1}$$

where $x[i]$ is the discrete EMG signal of window size N.

$$F2 = log(\sum_{i=0}^{N-1}[x[i]]^2) = log(\frac{1}{N}\sum_{k=0}^{N-1}[X[k]X^*[k]]) = log(\sum_{k=0}^{N-1}P[k]) \tag{2}$$

where $P[k]$ is the power spectrum, and $X^*[k]$ is the complex conjugate of $X[k]$ with a frequency index of k.

$$F3 = log(\sum_{k=0}^{N-1}k^2P[k]) = log(\frac{1}{N}\sum_{k=0}^{N-1}[kX[k]]^2) = log(\sum_{i=0}^{N-1}[\Delta x[i]]^2) \tag{3}$$

$$F4 = log(\sum_{k=0}^{N-1}k^4P[k]) = log(\frac{1}{N}\sum_{k=0}^{N-1}[k^2X[k]]^2) = log(\sum_{i=0}^{N-1}[\Delta^2 x[i]]^2) \tag{4}$$

TABLE 18. Selected features for training classifiers with O2 with a low force level and testing with O2 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	4	C1AcF, C2F8, C3AcF, C3F1	C1F1, C2F1, C3F1, C4F1	C1AcF, C3AcF, C2AcF, C1F1	C2AcF, C3AR1, C2AR4, C1AR15	C2AR6, C2AR7, C2AR5, C1F2
S2	13	C4F7, C3F1, C2AR1, C1AcF, C3AR1, C3AcF, C5F7, C2F2, C1F6, C4F3, C2AcF, C4AR14, CC10	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3, C4F3, C5F3, C6F3	C3AcF, C2AcF, C2F1, C6F6, C6F9, C6F5, C1F6, C3F1, C6F8, C6F4, C1F5, C2F2, C1F9	C4F7, C2AR6, C3AR13, C6AR14, C1AR15, C4AR15, C6F9, C3F6, C5AR3, C5AR15, CC2, C4AR2, C1AR2	C3AR8, C3AR7, C3AR9, C2AR8, C2AR7, C3AR10, C2AR9, C3AR6, C1AR7, C1AR6, C2AR10, C2AR6, C1AR5
S3	7	C1F8, C2F8, C3AcF, C5F2, C3F1, C5F3, C1F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C3AcF, C2AcF, C2F2, C2F1, C5F4, C5F5, C5F6	C1F7, C2AcF, C2F7, C3AR14, C2AR15, C5AR14, CC3	C1F5, C1F6, C1F4, C1F3, C1F2, C5F4, C5F5
S4	11	C3F1, C2F1, C3AcF, C1AcF, C1F5, C5F6, C3F9, C6F3, C5F1, C1F7, C1AR8	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2	C1AcF, C3AcF, C2AcF, C1F7, C1F1, C1F2, C1F3, C2F2, C2F1, C3F1, C3F2	C3F1, C5F3, C6AR14, C4AR15, C1AR15, C2AR14, CC10, C1F8, CC8, C2AcF, C1AR4	C1F3, C1F4, C2F2, C4F3, C2F3, C1F5, C4F4, C1F6, C4F5, C5F3, C4F6
S5	12	C1AcF, C1F8, C2F1, C2AcF, C5F5, C6F9, C3AcF, C3F8, C3F7, C3AR13, C1F3, C6AR7	C1F1, C2F1, C3F1, C1F2, C2F2, C3F2, C5F2, C1F3, C2F3, C3F3, C5F3, C1F4	C3AcF, C1AcF, C2AcF, C3F2, C3F1, C3F3, C2F1, C3F7, C5F4, C5F8, C3F4, C5F5	C1F7, C3AcF, C1AR4, CC13, C5AR13, C3AR15, CC7, C2AR13, C3F6, C5F7, C3AR4, C4AR6	C1F6, C1F5, C1F3, C1F4, C3F2, C3F3, C4F5, C4F4, C3F4, C3F6, C3F5, C2F2
S6	7	C4F8, C2F1, C1AcF, C1F5, C3F6, C6F1, C2F7	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C1AcF, C3AcF, C2AcF, C4F1, C4F2, C4F8, C4F7	C4F8, CC3, C6AR1, C3AR14, C2AR15, C4AR15, C5AR15	C3AR6, C2F3, C2F4, C2F2, C2F5, C2F6, C3AR5
S7	6	C1F8, C3F9, C3AcF, C5F2, C4F3, C3F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C3AcF, C1AcF, C2AcF, C2F7, C2F1, C3F7	C1F3, C6F5, C5AR14, C3AR14, C4AR13, C2AR14	C4F2, C3F4, C3F3, C4F3, C3F5, C3F6
S8	5	C3F8, C1AcF, C1F5, C4F9, C1F3	C1F1, C2F1, C3F1, C4F1, C5F1	C1F3, C1F7, C1F4, C1F8, C1F5	C3F6, C6F3, C4AR5, C2AR15, C1AR14	C3F4, C3F5, C3F6, C3F3, C3F2
S9	8	C1F1, C5F4, CC3, C5F2, C2F2, C1F6, C3AR5, C2F7	C1F1, C2F1, C3F1, C5F1, C1F2, C2F2, C3F2, C5F2	C3AcF, C1AcF, C2F8, C2F9, C2F7, C2F4, C1F7, C2F3	C5F4, C1F3, C6F4, C3AR12, C6AR15, C1AR15, C2AR14, CC10	C5F6, C5F5, C5F4, C5F3, C1F2, C5F2, C1F3, C1F4
S10	4	C1AcF, C1F3, C2AcF, C1AR2	C1F1, C3F1, C5F1, C1F2	C3AcF, C1AcF, C2AcF, C5F2	C1AcF, C1AR1, C6F7, CC3	C3F4, C3F5, C3F6, C3F3

$$F5 = log(\sum_{k=0}^{N-1} k^6 P[k]) = log(\frac{1}{N}\sum_{k=0}^{N-1}[k^3 X[k]]^2) = log(\sum_{i=0}^{N-1}[\Delta^3 x[i]]^2) \quad (5)$$

$$F6 = log(\sum_{k=0}^{N-1} k^8 P[k]) = log(\frac{1}{N}\sum_{k=0}^{N-1}[k^4 X[k]]^2) = log(\sum_{i=0}^{N-1}[\Delta^4 x[i]]^2) \quad (6)$$

$$F7 = log(\frac{1}{N-1}\sum_{i=0}^{N-1}|\Delta x|) \quad (7)$$

$$F8 = log(\frac{1}{N-2}\sum_{i=0}^{N-1}|\Delta^2 x|) \quad (8)$$

$$F9 = log(\frac{1}{N-3}\sum_{i=0}^{N-1}|\Delta^3 x|) \quad (9)$$

In our proposed feature selection method, the feature calculated for each EMG channel was considered a unique feature denoted as CJFI. Where C, J, F, and I indicate the channel, channel number (J = 1, 2, 3, ...6), feature name, and the feature number (I = 1, 2, 3, ...9), respectively.

The CC $p(x,y)$ between any two channels, x, and y, was evaluated as follows:

$$\rho(x,y) = \frac{Cov(x,y)}{\sigma_x\sigma_y} = \frac{\sum_{i=0}^{N-1}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=0}^{N-1}(x_i-\overline{x})^2}\sqrt{\sum_{i=0}^{N-1}(y_i-\overline{y})^2}} \quad (10)$$

where $\overline{x}$ and $\overline{y}$ present the mean of channels x and y for a window size of N, respectively. Here, CCs are presented as CC1, CC2, CC3, ...CC15.

The autoregressive (AR) coefficients are a promising feature extraction method for EMG-PR [41], [42]. So, we also considered 15 order AR coefficients to find their importance in resolving forearm orientation and muscle force variation. In the AR model, each sample of the EMG signal x_i is

TABLE 19. Selected features for training classifiers with O2 with a medium force level and testing with O2 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	6	C2AcF, C2F6, C1AcF, CC9, C3AcF, C2F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C6F2	C2AcF, C3AR1, C2AR4, C1AR15, CC12, CC5	C5AR8, C2AR7, C4AR8, C3AR7, C4AR7, C2AR6
S2	8	C3AcF, C4F1, C3F1, C2F1, C4F6, C3F2, CC12, C2F2	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2	C3AcF, C2AcF, C2F1, C6F6, C6F9, C6F5, C1F6, C3F1	C4F7, C2AR6, C3AR13, C6AR14, C1AR15, C4AR15, C6F9, C3F6	C3AR8, C3AR7, C3AR9, C2AR8, C2AR7, C3AR10, C2AR9, C3AR6
S3	6	C5F4, C1F9, C3F1, C2F4, C2AcF, C5F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C3AcF, C2AcF, C2F2, C2F1, C5F4, C5F5	C1F7, C2AcF, C2F7, C3AR14, C2AR15, C5AR14	C6AR7, C2AR8, C1AR7, C6AR9, C3AR9, C5AR7
S4	15	C3F1, C2F2, C3AcF, C1AcF, CC7, C5AR11, C3F2, C2F1, C3AR10, C2F7, C1F3, C4F6, C2AR15, C3F3, CC15	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3	C1AcF, C3AcF, C2AcF, C1F7, C1F1, C1F2, C1F3, C2F2, C2F1, C3F1, C3F2, C1F8, C2F7, C1F4, C3F3	C3F1, C5F3, C6AR14, C4AR15, C1AR15, C2AR14, CC10, C1F8, CC8, C2AcF, C1AR4, CC11, C3AcF, C1AcF, CC1	C2F3, C4F3, C4F2, C1F3, C2F4, C2F2, C4F4, C2F5, C2F6, C1F4, C4F5, C1F5, C4F6, C1F6, C3F2
S5	11	C1AcF, C1F7, C3AcF, C2F1, C5F7, C3F9, C1F8, C1F9, CC10, C3F6, C3F5	C1F1, C2F1, C3F1, C1F2, C2F2, C3F2, C5F2, C1F3, C2F3, C3F3, C5F3	C3AcF, C1AcF, C2AcF, C3F2, C3F1, C3F3, C2F1, C3F7, C5F4, C5F8, C3F4	C1F7, C3AcF, C1AR4, CC13, C5AR13, C3AR15, CC7, C2AR13, C3F6, C5F7, C3AR4	C3F2, C3F3, C3F4, C3F6, C3F5, C1F4, C1F5, C1F6, C1F3, C2F2, C2F3
S6	13	C4F9, C2F2, C1AcF, C3F2, C6F7, C1F5, C2F1, C3F6, C2F7, C1F3, C3F5, C1F8, C1F6	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3	C1AcF, C3AcF, C2AcF, C4F1, C4F2, C4F8, C4F7, C4F3, C4F4, C4F9, C3F4, C3F3, C3F5	C4F8, CC3, C6AR1, C3AR14, C2AR15, C4AR15, C5AR15, CC4, C2AcF, C1AcF, C6F9, CC14, CC6	C2F3, C2F2, C2F4, C2F5, C2F6, C4F4, C4F3, C4F5, C4F6, C4F2, C1F3, C1F4, C1F5
S7	7	C1F3, C4F5, C3AcF, C3F1, C1F1, C5F1, C4F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C3AcF, C1AcF, C2AcF, C2F7, C2F1, C3F7, C2F8	C1F3, C6F5, C5AR14, C3AR14, C4AR13, C2AR14, C2AcF	C4F4, C4F5, C4F3, C4F6, C4F2, C1F3, C3F3
S8	5	C1F2, C1AcF, C3F7, C4F1, C1F3	C1F1, C2F1, C3F1, C4F1, C5F1	C1F3, C1F7, C1F4, C1F8, C1F5	C3F6, C6F3, C4AR5, C2AR15, C1AR14	C3F4, C3F5, C3F3, C3F6, C4F3
S9	14	C5F4, C2F1, C1F7, C5F7, C3F4, C5AR1, CC10, C5F3, C3AcF, C1AcF, C2F5, C5AR9, C5F1, C5F2	C1F1, C2F1, C3F1, C5F1, C1F2, C2F2, C3F2, C5F2, C1F3, C2F3, C3F3, C5F3, C1F4, C2F4	C3AcF, C1AcF, C2F8, C2F9, C2F7, C2F4, C1F7, C2F3, C2F5, C2F6, C1F8, C1F1, C2F2, C2F1	C5F4, C1F3, C6F4, C3AR12, C6AR15, C1AR15, C2AR14, CC10, CC1, CC4, C4AR14, CC5, C3AcF, C5AR14	C5F3, C5F4, C5F5, C5F2, C5F6, C3AR8, C1F3, C1F2, C3AR7, C1F4, C2AR8, C2AR7, C1F5, C3AR9
S10	7	C1AcF, C3F6, C5F5, C1F4, C3AcF, C6AR1, C1F3	C1F1, C3F1, C5F1, C1F2, C2F2, C3F2, C5F2	C3AcF, C1AcF, C2AcF, C5F2, C5F3, C5F5, C5F4	C1AcF, C1AR1, C6F7, CC3, C5AR14, C2AR13, C6AR15	C3F4, C3F5, C3F3, C3F6, C3F2, C2F3, C2F4

presented as a linear combination of the previous samples x_{i-p} and a white noise error w_i as follows:

$$x_i = \sum_{p=1}^{P} a_p x_{i-p} + w_i \tag{11}$$

where P is the order of AR coefficients, fifteen order AR coefficients for multichannel EMG signals are presented as CJARP where P = 1, 2, 3, ... 15.

In addition to these features, we also calculated the RMS feature for 3-D accelerometer data, which are presented as C1AcF, C2AcF, and C3AcF. Finally, total number of features became 162 (6 channels $\times$ (9 features + 15 AR coefficients) + 15 correlation coefficients + 3 accelerometer features).

D. CLASSIFICATION

In this study, we utilized MATLAB 2020a (MathWorks, USA) for evaluating the EMG-PR performance. First, the EMG signal was segmented using disjoint rectangular windowing for 150 ms [15], [43]. Thus, three trials of 15 s duration provided 100 samples, and each subject provided 600 samples per forearm orientation and muscle force level (6 movements $\times$ 100 samples). Then, we extracted 162-dimensional features for each sample as described in Section II-C. The high dimensional features were fed to the proposed feature selection method (Section II-A), which only identifies the efficient features. In this research, selected features were lied between 3 to 20 without compromising the EMG-PR performance (Table 15 to Table 30). However, to evaluate the EMG-PR performance, we considered three well-recognized classifiers, namely KNN with Euclidean distance and ten neighbors, SVM with a Gaussian radial basis function, and kernel scale=3, and LDA [14], [24], [43]. In this optimization, we employed the '*Classification Learner*' app of MATLAB 2020a and the selected feature space of S1 from the proposed feature selection method considering the best training orientation, O2, with the best training force level, medium (Section III). We employed one orientation and one

TABLE 20. Selected features for training classifiers with O2 with a high force level and testing with O2 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	6	C5F1, C2AcF, C1AcF, CC13, C2F4, C3F6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C6F2	C2AcF, C3AR1, C2AR4, C1AR15, CC12, CC5	C1F2, C6F2, C1F3, C4F3, C4F4, C1F4
S2	7	C4F7, C3F1, C1F6, C3F3, C3AcF, C5F7, C3AR7	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2	C3AcF, C2AcF, C2F1, C6F6, C6F9, C6F5, C1F6	C4F7, C2AR6, C3AR13, C6AR14, C1AR15, C4AR15, C6F9	C4AR7, C3AR7, C6AR7, C3AR8, C6AR8, C2AR9, C5AR7
S3	8	C1F8, C5F3, C4F9, C3F1, C2F5, C3AcF, C4F1, C5F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C3AcF, C2AcF, C2F2, C2F1, C5F4, C5F5, C5F6, C5F3	C1F7, C2AcF, C2F7, C3AR14, C2AR15, C5AR14, CC3, C3F1	C2AR8, C3AR6, C5AR7, C2AR7, C4AR7, C1AR7, C1AR8, C2AR10
S4	8	C4F2, C2F1, C2AcF, C3F3, C3AcF, C1F7, C5AR12, C3F7	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C1AcF, C3AcF, C2AcF, C1F7, C1F1, C1F2, C1F3, C2F2	C3F1, C5F3, C6AR14, C4AR15, C1AR15, C2AR14, CC10, C1F8	C4F3, C3F2, C1F3, C3F3, C4F2, C4F4, C2F2, C1F4
S5	10	C1AcF, C1F3, C2AcF, C2F1, C6F5, C3F3, C3AcF, C5F8, C1AR15, C5AR15	C1F1, C2F1, C3F1, C1F2, C2F2, C3F2, C5F2, C1F3, C2F3, C3F3	C3AcF, C1AcF, C2AcF, C3F2, C3F1, C3F3, C2F1, C3F7, C5F4, C5F8	C1F7, C3AcF, C1AR4, CC13, C5AR13, C3AR15, CC7, C2AR13, C3F6, C5F7	C3F5, C3F4, C3F3, C3F6, C3F2, C2F2, C1F2, C4F3, C2F3, C5F4
S6	7	C4F8, C2F1, C1AcF, C3F8, C1F9, C1F6, C1F5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C1AcF, C3AcF, C2AcF, C4F1, C4F2, C4F8, C4F7	C4F8, CC3, C6AR1, C3AR14, C2AR15, C4AR15, C5AR15	C4F3, C4F4, C4F2, C4F5, C2F2, C4F6, C2F3
S7	6	C1F3, C4F8, C3AcF, C3F8, C4F1, C3F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C3AcF, C1AcF, C2AcF, C2F7, C2F1, C3F7	C1F3, C6F5, C5AR14, C3AR14, C4AR13, C2AR14	C4F6, C4F5, C4F4, C4F3, C3F3, C4F2
S8	8	C1F2, C1AcF, C3F9, C4F3, CC9, C6F5, C5F3, C1F5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C1F3, C1F7, C1F4, C1F8, C1F5, C1F9, C1F2, C1F6	C3F6, C6F3, C4AR5, C2AR15, C1AR14, C2F9, C1AR1, CC4	C3F5, C3F4, C3F6, C3F3, C4F4, C4F3, C4F5, C4F6
S9	11	C5F4, C2F2, C5AR3, C2F4, C1F9, C3F3, C5F1, C1F7, C5F3, C5AR4, C5AR2	C1F1, C2F1, C3F1, C5F1, C1F2, C2F2, C3F2, C5F2, C1F3, C2F3, C3F3	C3AcF, C1AcF, C2F8, C2F9, C2F7, C2F4, C1F7, C2F3, C2F5, C2F6, C1F8	C5F4, C1F3, C6F4, C3AR12, C6AR15, C1AR15, C2AR14, CC10, CC1, CC4, C4AR14	C2AR6, C4AR6, C1AR8, C3AR7, C3AR8, C2AR9, C6AR8, C2AR8, C4AR7, C5AR8, C4AR8
S10	6	C1F7, C1AcF, C2AcF, C3F6, C5F2, C1AR11	C1F1, C3F1, C5F1, C1F2, C2F2, C3F2	C3AcF, C1AcF, C2AcF, C5F2, C5F3, C5F5	C1AcF, C1AR1, C6F7, CC3, C5AR14, C2AR13	C5AR10, C5AR9, C3AR9, C3AR10, C6AR7, C3AR8

force level to achieve forearm orientation and force invariant EMG-PR. Also, we employed 5-fold cross-validation to evaluate EMG-PR performance and avoid data overfitting problems. This 5-fold cross-validation considering forearm orientation and/or muscle force invariant properties confirmed that unknown testing samples never mixed with the training samples. To carry out this special 5-fold cross-validation, known samples were conventionally divided into training and testing samples. Unknown testing samples were also divided using 5-fold cross-validation, with the only unknown testing fold added to the known testing samples. To compare and validate the proposed feature selection method, we considered four existing feature selection methods, chi-square [25], ReliefF [26], MRMR [27], and NCA [26]. In these existing feature selection methods, the least number of features defined by the proposed feature selection method was also selected for chi-square, ReliefF, MRMR, and NCA. Depending upon the feature ranking considering $K = I \times J$ number of unique features for a I number of features extracted from J number of EMG channels and all samples as employed in the proposed feature selection method. Thus, we selected the same number of features for the existing four feature selection methods. In addition, to analyze the EMG-PR performance in different aspects, we considered six statistical parameters, accuracy, sensitivity, specificity, precision, F1 score, and MCC [14], [31]. These parameters are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

$$Precision = \frac{TP}{TP + FP} \tag{15}$$

$$F1\ Score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \tag{16}$$

$$MCC = \frac{TN \times TP - FN \times FP}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{17}$$

where TP, TN, FP, and FN define the number of the true positive movements, the true negative movements, the false

TABLE 21. Selected features for training classifiers with O3 with a low force level and testing with O3 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	8	C1AcF, C1F1, C2F9, C2AcF, CC6, C3AcF, C2F1, C1F3	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F4, C1F8, C1F7	C1AcF, C5F2, C1AR3, CC5, C3AR15, C2AR15, C6AR10, CC14	C1F3, C1F2, C1F4, C5F2, C5F3, C1F5, C1F6, C5F4
S2	6	C2AcF, C3F1, C2F1, C6F5, C4F6, C1AcF	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2	C2AcF, C1AcF, C3AcF, C3F1, C3F7, C3F2	C1AcF, C1F4, C6F7, C4AR2, C2AR15, CC4	C3F3, C3F2, C3F4, C3F5, C4F2, C3F6
S3	4	C2AcF, C3F1, C5F6, C3AcF	C1F1, C2F1, C3F1, C4F1	C2AcF, C1AcF, C1F4, C1F8	C2AcF, C1F3, C3F3, C6AR14	C3AR6, C3AR7, C3AR5, C4F3
S4	9	C4F2, C2F2, C3F7, C3AcF, C2F1, C4F8, C1F2, C1AR15, C3F6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C3AcF, C2F2, C2F1, C2F3, C2F7, CC10, C1AcF, C2F4	C3F7, C2F3, C3AR1, C2AR14, CC9, CC7, C2AcF, C6AR15, CC4	C2F2, C1F3, C2F3, C3F3, C3F4, C3F2, C3F5, C2F4, C1F2
S5	18	C1F7, C3F2, C6F1, C1F6, C2F1, C1F8, C3F4, C2AcF, CC9, C3F5, C6F2, C1AcF, C5F1, C3F9, C3F6, C1F9, C3F1, C1F5	C1F1, C3F1, C1F2, C3F2, C1F3, C3F3, C5F3, C1F4, C3F4, C5F4, C1F5, C3F5, C5F5, C1F6, C3F6, C5F6, C1F7, C3F7	C2AcF, C1AcF, C3F2, C3F3, C3F1, C1F2, C3F4, C3F5, C3F6, C1F1, C3F7, C5F2, C5F3, C5F1, C3F8, C2F1, C1F3, C3F9	C1F3, C1AcF, C3AR1, C2AR11, CC7, C6AR15, C4AR15, CC6, C3AcF, CC1, C1AR14, C3F2, C6F9, C4F4, C2F1, C2AcF, CC11, CC8	C3F6, C3F3, C3F5, C3F4, C3F2, C1F6, C1F5, C1F4, C1F3, C1F2, C3F7, C3F9, C3F8, C3F1, C1F9, C5F4, C1F8, C2F2
S6	9	C4F2, C2F1, C3F9, C6F7, C2AcF, C4AR6, C1F4, C1F2, C1F1	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C4F1, C4F2, C4F7, CC6, C3F2, C4F3, C3F3, C4F8	C4F3, C2AcF, CC11, C3AR12, CC4, C5AR15, C1AR14, C4AR15, C2AR13	C4F2, C4F3, C6F6, C6F5, C6F4, C6F3, C3F3, C6F2, C4F4
S7	12	C4F9, C3F9, C3AcF, C5F4, C1F2, C4AR1, C2F4, C3F1, C4F1, C1F8, C4F2, CC13	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3	C2AcF, C3AcF, C1AcF, C3F1, C3F7, C3F8, C3F2, C3F3, C3F4, C3F9, C3F5, C3F6	C4F4, C2F1, C2AR1, C3AR14, C1AR14, C4AR15, C6AR15, C3AR1, C5AR15, CC12, CC2, C5AR4	C4F2, C4F6, C4F3, C4F4, C4F5, C3F6, C3F5, C5F3, C3F4, C3F3, C5F4, C5F2
S8	9	C1F2, C5F2, C3F9, C6F1, C2F1, C5F9, C1F9, C3F1, C2F7	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C2AcF, C1AcF, C2F1, C2F2, C6F5, C6F4, C6F6, C6F9, C6F8	C3F7, C4F3, CC2, C3AR14, C6AR15, C1AR15, C2AR15, C4AR15, C6F3	C3AR7, C6AR8, C1AR9, C3F4, C6AR7, C3F3, C3F5, C6AR9, C3F6
S9	16	C3AcF, C2F3, C1AcF, C2AcF, C2AR4, C3F1, C5F6, C3AR1, C1F1, C3F2, C6AR3, C5F8, C1AR15, C6F1, C1F7, C6AR15	C1F1, C2F1, C5F1, C6F1, C1F2, C2F2, C3F2, C5F2, C6F2, C1F3, C2F3, C4F3, C5F3, C6F3, C1F4, C2F4	C1AcF, C2AcF, C2F7, C2F8, C2F1, C2F2, C2F9, C2F3, C2F4, C2F5, C3AcF, C2F6, C1F1, C1F7, C1F6, C1F5	C2F3, C2AcF, C6F6, C2AR14, C3AR14, CC12, C4AR15, C6AR15, C5AR15, CC10, C1AR14, CC1, CC2, C1AR3, CC14, C2AR6	C1F3, C1F4, C1F2, C1F5, C1F6, C2F6, C2F5, C2F4, C2F3, C2F2, C4F3, C4F6, C4F4, C4F5, C4F2, C6F2
S10	10	C2AcF, C4F6, C1F7, C4AR1, C5AR10, C1F3, C3AcF, C1F1, C1F8, C4AR8	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3	C2AcF, C1F4, C1F5, C1F7, C1F8, C1F3, C1F6, C1F9, C1F1, C1F2	C1F7, C4AR1, C2AR10, CC12, C6AR15, C5AR15, CC2, C6F8, CC14, C3F5	C1AR7, C4AR7, C3AR7, C5AR9, C6AR8, C2AR10, C2AR9, C6AR7, C3AR8, C5AR7

positive movements, and the false negative movements, respectively. This research considered four cases of training the classifiers to evaluate forearm orientation and muscle force invariant EMG-PR performance. These are as follows:

Case 1: Training for one orientation with one force level.

Case 2: Training for one orientation with a medium force level.

Case 3: Training for two orientations with a medium force level.

Case 4: Training for all orientations with a medium force level.

E. STATISTICAL TEST

To find the significant difference between any pairs of feature selection methods, we employed two-way ANOVA. The independent variables were classifiers and feature selection methods, and the dependent variable was the F1 score. In this statistical test, we included Bonferroni correction with a threshold level of 5%. The obtained p-values below 0.05 imply that the performance is significant. In this research, the subject-wise F1 score under three training and testing cases (training and testing cases in each table, Table 1 to Table 3) was concatenated to form a 30-dimensional vector (10 subjects $\times$ 3 training and testing cases), and two-way ANOVA was performed.

III. RESULTS

A. IMPACT OF THE NUMBER OF FEATURES AND FEATURE SELECTION METHODS ON EMG-PR PERFORMANCE

To show the impact of the number of features and different feature selection methods on the F1 score, we considered the KNN, SVM, and LDA classifiers. However, these impacts using KNN are shown in Fig. 2. In this study, we employed S1, where the classifiers were trained

TABLE 22. Selected features for training classifiers with O3 with a medium force level and testing with O3 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	7	C1AcF, C1F1, C2F7, C3F9, C4F9, C3AR1, C4F6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F4, C1F8	C1AcF, C5F2, C1AR3, CC5, C3AR15, C2AR15, C6AR10	C1F3, C1F2, C1F4, C5F3, C1F5, C5F4, C5F2
S2	9	C2AcF, C2F2, C5F4, C4F2, C1AcF, C2F9, C4F1, CC10, C2F6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C1AcF, C3AcF, C3F1, C3F7, C3F2, C3F3, C3F8, C4F2	C1AcF, C1F4, C6F7, C4AR2, C2AR15, CC4, C1AR15, CC1, CC15	C4F3, C4F4, C3F3, C4F5, C4F2, C3F6, C3F5, C3F4, C4F6
S3	10	C2AcF, C1F2, C3F1, C5F2, CC6, C5AR1, CC9, C5F6, C3AcF, C4F4	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C1AcF, C1F4, C1F8, C1F3, C1F7, C1F5, C1F9, C1F6, C1F1	C2AcF, C1F3, C3F3, C6AR14, C4AR14, C2AR14, C5AR15, C1AR15, C3AR15, C3AR3	C4F3, C1F3, C4F4, C4F5, C1F4, C1F2, C4F6, C4F2, C1F5, C1F6
S4	7	C4F2, C2F1, C2AcF, C3F2, C1F2, C2F2, C4F4	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C2AcF, C3AcF, C2F2, C2F1, C2F3, C2F7, CC10	C3F7, C2F3, C3AR1, C2AR14, CC9, CC7, C2AcF	C2F2, C2F3, C2F4, C4F2, C4F4, C4F3, C2F5
S5	11	C1F6, C3F6, C5F9, C2AcF, C6F1, C6F5, C1F8, C3F5, C1F1, C1F9, C5F4	C1F1, C3F1, C1F2, C3F2, C1F3, C3F3, C5F3, C1F4, C3F4, C5F4, C1F5	C2AcF, C1AcF, C3F2, C3F3, C3F1, C1F2, C3F4, C3F5, C3F6, C1F1, C3F7	C1F3, C1AcF, C3AR1, C2AR11, CC7, C6AR15, C4AR15, CC6, C3AcF, CC1, C1AR14	C3F6, C3F5, C3F4, C3F2, C3F3, C1F4, C1F5, C1F3, C1F6, C5F3, C5F2
S6	13	C4F2, C3F8, C6F6, C2F8, C1AR9, C2F9, C1F3, C6F1, C2AR1, CC3, C1F8, C1F7, CC1	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2, C2F2, C3F2, C4F2, C6F2, C1F3, C2F3, C3F3	C2AcF, C4F1, C4F2, C4F7, CC6, C3F2, C4F3, C3F3, C4F8, C4F4, C3F1, C4F9, C4F5	C4F3, C2AcF, CC11, C3AR12, CC4, C5AR15, C1AR14, C4AR15, C2AR13, CC13, CC6, C6AR14, CC7	C3F3, C6F6, C6F5, C3F4, C6F4, C3F2, C6F3, C3F5, C3F6, C6F2, C4F2, C4F3, C1F6
S7	9	C4F9, C3F9, C5F2, C4F1, C2F4, C1F4, C3F1, C4F4, C2F5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C3AcF, C1AcF, C3F1, C3F7, C3F8, C3F2, C3F3, C3F4	C4F4, C2F1, C2AR1, C3AR14, C1AR14, C4AR15, C6AR15, C3AR1, C5AR15	C4F3, C3F6, C4F4, C3F5, C4F5, C4F2, C4F6, C3F4, C3F3
S8	10	C1F2, C3F1, C5F1, C2F1, C6F8, C2AR1, C1F7, C2F2, C1F3, C1F4	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C1AcF, C2F1, C2F2, C6F5, C6F4, C6F6, C6F9, C6F8, C6F7	C3F7, C4F3, CC2, C3AR14, C6AR15, C1AR15, C2AR15, C4AR15, C6F3, C2AR6	C2AR7, C6AR6, C4AR7, C3AR9, C4AR6, C4AR8, C3AR7, C6AR7, C2AR8, C3AR8
S9	7	C2AcF, C1AcF, C5F9, C6F7, C1F3, C3AR10, CC6	C1F1, C2F1, C5F1, C6F1, C1F2, C2F2, C3F2	C1AcF, C2AcF, C2F7, C2F8, C2F1, C2F2, C2F9	C2F3, C2AcF, C6F6, C2AR14, C3AR14, CC12, C4AR15	C1F3, C1F2, C1F4, C2F6, C2F5, C2F4, C1F5
S10	12	C2AcF, C3F3, C1AcF, C5F9, C1F6, C3AR2, C4F1, C3F2, C1F5, C4F7, C2F6, C3AcF	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3, C4F3, C5F3	C2AcF, C1F4, C1F5, C1F7, C1F8, C1F3, C1F6, C1F9, C1F1, C1F2, C5F6, C5F5	C1F7, C4AR1, C2AR10, CC12, C6AR15, C5AR15, CC2, C6F8, CC14, C3F5, C4AR14, CC5	C1AR8, C4F4, C4F3, C4AR8, C4F5, C1AR7, C4F6, C4AR7, C5AR5, C4F2, C6AR8, C2AR8

with O2 with a medium force level and tested with O2 with all force levels. The figure indicated that the F1 score of the existing feature selection methods fluctuated with the number of features. These fluctuating characteristics implied that all features did not contribute to enhancing the F1 score; instead, some of the features played a negative role in the EMG-PR performance. Again, it was clear from Fig. 2 that the proposed feature selection method achieved 100% F1 score using only 6 efficient features. It was about 4% to 5% higher F1 scores than the existing methods, where chi-square, ReliefF, MRMR, and NCA achieved the highest F1 score of 95.11%, 95.59%, 95.87%, and 94.96% using 157, 4, 56, and 136 features, respectively. It could be noted here that the other two classifiers, SVM and LDA, also followed KNN. So, the proposed feature selection method would be able to select the least number of features with improved EMG-PR performance for forearm orientation and muscle force invariant EMG-PR.

B. TRAINING FOR ONE ORIENTATION WITH ONE FORCE LEVEL (CASE 1)

To find the force invariant properties of the proposed feature selection method, we trained the classifiers for one orientation with one force level and tested the classifiers for trained orientation with all force levels. The force invariant EMG-PR performances for each orientation, O1, O2, and O3, are shown in Table 1. The summary of the tables is shown in Fig. 3a, Fig. 3b, and Fig. 3c, where only F1 scores with standard deviation across the subjects are plotted. The experimental results indicated that the proposed feature selection method overperformed existing methods considered in terms of performance and standard deviation. The force invariant EMG-PR performance was highest when the KNN classifier was trained with O2 with a medium force level. In this best training arrangement, the proposed feature selection method achieved the highest accuracy, sensitivity, specificity, precision, F1 score, and MCC of 99.34%, 98.01%,

TABLE 23. Selected features for training classifiers with O3 with a high force level and testing with O3 with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	11	C1AcF, C1F1, C2F8, C4F4, C1AR1, C3AR3, C3F6, CC6, C1F8, C2F9, C4AR3	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F4, C1F8, C1F7, C1F3, C1F9, C1F5	C1AcF, C5F2, C1AR3, CC5, C3AR15, C2AR15, C6AR10, CC14, C4F1, CC7, C1AR15	C1F3, C1F2, C1F4, C1F5, C1F6, C5F4, C5F3, C5F5, C5F6, C5F2, C1F7
S2	17	C2AcF, C2F7, C3F4, C4F8, C6F6, C1F6, C2F1, C4AR1, C3AcF, C1AcF, C4AR4, C4AR3, C6F9, CC3, C4AR14, CC1, C4AR5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3	C2AcF, C1AcF, C3AcF, C3F1, C3F7, C3F2, C3F3, C3F8, C4F2, C4F1, C4F3, C3F4, C4F7, C3F9, C3F5, C3F6, C4F4	C1AcF, C1F4, C6F7, C4AR2, C2AR15, CC4, C1AR15, CC1, CC15, C3AR14, C2AR7, C4AR15, CC3, C5F5, C4F9, CC7, C3AcF	C6AR9, C3AR7, C4AR8, C4AR9, C6AR8, C1AR7, C3AR8, C3AR6, C2AR7, C2AR8, C6AR7, C1AR6, C2AR6, C5AR8, C4AR7, C1AR9, C5AR7
S3	19	C4F7, C2F8, C1F6, C5F7, C2AcF, C1F7, C3F1, C1F2, C3AR8, C3F2, C5F3, CC2, C4AR14, C5F8, C3AR13, C1AcF, C6F7, CC6, C6F8	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4	C2AcF, C1AcF, C1F4, C1F8, C1F3, C1F7, C1F5, C1F9, C1F6, C1F1, C1F2, C2F1, C3F1, C2F2, C3F7, C3F8, C3F2, C3F5, C3F9	C2AcF, C1F3, C3F3, C6AR14, C4AR14, C2AR14, C5AR15, C1AR15, C3AR15, C3AR3, C6F5, CC3, CC4, CC1, C2AR3, C1F9, C3AcF, CC2, CC6	C4AR8, C4AR9, C5AR7, C5AR8, C4F3, C4AR7, C4F4, C4F5, C4F6, C4F2, C5AR9, C4AR10, C5F5, C5F4, C1F6, C5F6, C1F5, C1F4, C5F3
S4	8	C2F2, C3F7, C2AcF, C1AR9, CC1, C4F1, C4F9, C2F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C2AcF, C3AcF, C2F2, C2F1, C2F3, C2F7, CC10, C1AcF	C3F7, C2F3, C3AR1, C2AR14, CC9, CC7, C2AcF, C6AR15	C2F2, C2F3, C1F3, C2F4, C1F2, C2F5, C2F6, C1F4
S5	11	C1F5, C3F3, C6F1, C2AcF, C1AcF, C2F7, C4F6, C3F2, C2F9, CC6, C3F4	C1F1, C3F1, C1F2, C3F2, C1F3, C3F3, C5F3, C1F4, C3F4, C5F4, C1F5	C2AcF, C1AcF, C3F2, C3F3, C3F1, C1F2, C3F4, C3F5, C3F6, C1F1, C3F7	C1F3, C1AcF, C3AR1, C2AR11, CC7, C6AR15, C4AR15, CC6, C3AcF, CC1, C1AR14	C1F3, C1F4, C3F6, C1F5, C3F5, C1F6, C3F4, C3F3, C3F2, C1F2, C5AR11
S6	10	C4F2, C3F2, C6F6, C3F4, C3F1, C2F1, C6F1, C2AcF, C1F7, C3F6	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2, C2F2, C3F2, C4F2, C6F2	C2AcF, C4F1, C4F2, C4F7, CC6, C3F2, C4F3, C3F3, C4F8, C4F4	C4F3, C2AcF, CC11, C3AR12, CC4, C5AR15, C1AR14, C4AR15, C2AR13, CC13	C3F3, C3F2, C3F4, C3F5, C3F6, C4F2, C4F3, C6F3, C4F4, C6F4
S7	8	C4F4, C3F9, C2F3, C4F1, C5F2, C4AR1, C4F6, C4F9	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C2AcF, C3AcF, C1AcF, C3F1, C3F7, C3F8, C3F2, C3F3	C4F4, C2F1, C2AR1, C3AR14, C1AR14, C4AR15, C6AR15, C3AR1	C4F2, C4F3, C4F5, C4F6, C4F4, C5F2, C3F6, C3F5
S8	9	C1F7, C3F2, C4F3, C5F7, C4F8, C2F3, C2F1, C2F9, C4F4	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C2AcF, C1AcF, C2F1, C2F2, C6F5, C6F4, C6F6, C6F9, C6F8	C3F7, C4F3, CC2, C3AR14, C6AR15, C1AR15, C2AR15, C4AR15, C6F3	C2F2, C6F4, C2F3, C6F5, C6F3, C6F6, C3F5, C3F4, C3F6
S9	17	C3AcF, C2F9, C6F2, C3F2, C1F3, C6AR10, C2AcF, C2AR1, C5F6, C1F7, C1F4, C4F9, C1AcF, C3AR11, C2AR14, C1F1, C6AR9	C1F1, C2F1, C5F1, C6F1, C1F2, C2F2, C3F2, C5F2, C6F2, C1F3, C2F3, C4F3, C5F3, C6F3, C1F4, C2F4, C4F4	C1AcF, C2AcF, C2F7, C2F8, C2F1, C2F2, C2F9, C2F3, C2F4, C2F5, C3AcF, C2F6, C1F1, C1F7, C1F6, C1F5, C1F4	C2F3, C2AcF, C6F6, C2AR14, C3AR14, CC12, C4AR15, C6AR15, C5AR15, CC10, C1AR14, CC1, CC2, C1AR3, CC14, C2AR6, C6AR2	C6AR7, C6AR6, C6AR8, C6AR5, C3AR10, C6AR4, C3AR9, C3AR11, C4AR8, C4AR9, C6AR9, C4AR7, C4AR10, C3AR8, C3AR12, C4F2, C4AR6
S10	10	C1F7, C4F6, C3F1, C5F6, C4AR7, C5AR4, C1AcF, C3F7, C2AcF, C5AR1	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3	C2AcF, C1F4, C1F5, C1F7, C1F8, C1F3, C1F6, C1F9, C1F1, C1F2	C1F7, C4AR1, C2AR10, CC12, C6AR15, C5AR15, CC2, C6F8, CC14, C3F5	C1F6, C1F5, C4F4, C4F3, C4F5, C1F4, C1F3, C4F6, C1F2, C4F2

99.60%, 98.14%, 98.02%, and 0.98, respectively, employing only 5 to 15 features (Table 19). Also, the proposed feature selection method improved the performances, accuracy, sensitivity, specificity, precision, F1 score, and MCC by 3.18%, 9.52%, 1.90%, 8.30%, 9.71%, and 0.11, respectively, when the performances were compared with the second-best performing method among the existing, i.e., chi-square. For the best-performing orientation, O2, we also evaluated p-values considering classifiers and feature selection methods (Table 6 and Table 7). The obtained p-values indicated that the F1 score significantly depended on the feature selection methods ($p \ll 0.001$) rather than the classifiers ($p=0.68$). In addition, the proposed feature selection method provided a significantly improved F1 score considering the existing four feature selection methods ($p \ll 0.001$). However, the experimental results indicated that the SVM classifier follows the KNN classifier, but another classifier, LDA, reported in various literature, provided relatively poor EMG-PR performance. Table 19 shows subject-wise selected features in this best training strategy for different feature selection methods.

TABLE 24. Selected features for training classifiers with O1 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	10	C3F2, CC9, C1AR3, C5F2, CC13, C3F1, C3F3, C3F7, CC6, C6AR12	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2	C1AcF, C3AcF, C1F1, C1F2, C2AcF, C1F7, C1F3, C1F4, C1F8, C1F5	C2F3, C3AcF, C1F7, CC4, C3AR15, C2AR15, C5AR15, C1AR15, CC9, C6AR14	C1F2, C1F3, C1F4, C4F2, C1F5, C5F2, C1F6, C5F3, C1AcF, C4F3
S2	13	C4F3, C5AR2, C1F2, C4F6, C5F2, C3AR10, C4F7, C3AR1, C2F9, C4F5, C4F8, C3AR4, C5AR9	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3	C2AcF, C1AcF, C3AcF, C3F1, C3F2, C3F7, C3F3, C3F4, C3F8, C3F5, C3F9, C3F6, C4F2	C2AcF, C3F5, C4AR1, C3AR13, C2AR14, CC4, C5AR15, C1AR15, C4AR15, CC1, C6AR14, C5F1, C2F1	C5F3, C3F2, C3F3, C5F4, C4F4, C4F3, C4F5, C4F6, C5F5, C5F2, C3F4, C2F5, C2F4
S3	12	C1F1, C3F3, C5F6, C2AR1, C4F1, C1F3, CC5, C3F1, C4AR12, C1F4, CC2, C1F9	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2	C2AcF, C3AcF, C1AcF, C1F3, C1F1, C1F2, C2F2, C1F7, C1F4, C1F8, C4F2, C3F1	C1F3, C2F3, C6AR5, C5AR15, C4AR15, C1AR15, CC1, C3F2, C2AR15, CC7, C3AR14, CC8	C1F3, C1F4, C1F5, C1F2, C1F6, C4F2, C4F3, C4F4, C4F6, C4F5, C5F3, C5F4
S4	15	C4F2, C1F6, C2F6, C1F2, C5F3, C1F7, C1F1, C2F3, C1F3, C4F6, CC5, CC10, C3AR15, C3F6, CC13	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3	C1AcF, C3AcF, C2AcF, C2F2, C2F1, C2F3, C2F7, C1F3, C1F2, C3F1, C1F7, C1F1, C3F2, C2F8, CC10	C1F2, C3AcF, C5AR12, C2AR14, C3AR15, C6AR15, CC8, C2F1, C4F6, CC3, C5F2, C4AR14, C1F9, CC10, C4F3	C1F3, C1F4, C1F5, C1F6, C2F2, C2F3, C4F3, C4F4, C2F4, C4F2, C4F5, C2F5, C5F3, C2F6, C1F2
S5	7	C1F5, C3F4, C5F3, C6F5, C4F2, CC10, CC15	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C2AcF, C3AcF, C1AcF, C3F2, C3F3, C3F1, C2F1	C1F5, C2AcF, CC6, C2AR9, CC2, C3AR15, C4AR15	C1F3, C1F5, C1F6, C1F4, C2AcF, C1F2, C3F6
S6	6	C4F5, C2F1, C3F2, C1F1, C2F2, C1F7	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2	C2AcF, C3AcF, C1AcF, C2F1, C4F2, C4F1	C4F3, C2AcF, C6AR1, CC3, C1AR13, C4AR15	C4F2, C4F3, C4F4, C4F5, C4F6, C3F3
S7	5	C1F2, C4F8, C3F7, C6F6, C3F6	C1F1, C2F1, C3F1, C4F1, C5F1	C2AcF, C1AcF, C3AcF, C3F1, C3F7	C4F6, C3AR1, C6AR8, C1AR15, C4AR15	C4F3, C4F4, C4F5, C4F2, C4F6
S8	13	C3F3, C2F6, C6F9, C3F9, CC8, C2AR5, C4F2, C1AR3, C2F7, C3F6, C2F8, CC3, C2AR14	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3	C2AcF, C3AcF, C1F2, C1F3, C6F2, C6F1, C1F7, C1F4, C1F5, C1F1, C1F8, C2F1, C1F6	C3F9, C6F1, C1AcF, C3AR14, C2AR15, C4AR15, C2AR1, CC7, CC8, C4AR4, C1F6, C2F7, CC9	C3AR7, C5AR7, C4AR6, C3AR9, C2AR6, C4AR10, C1AR9, C3AR10, C1AR8, C2AR8, C6AR8, C3F4, C3F3
S9	16	C5F4, C2F2, C2F9, C3F3, C1F3, C2AR6, C6AR13, CC10, C2F8, C2AR15, C2F5, CC13, C1F7, C3F2, CC3, C3F6	C1F1, C2F1, C3F1, C5F1, C6F1, C1F2, C2F2, C3F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3	C2AcF, C3AcF, C1AcF, C2F8, C2F9, C2F7, C2F3, C2F1, C2F4, C2F2, C2F5, C2F6, C1F1, C1F7, C1F2, C1F3	C5F7, C1F7, C3AR13, C6AR15, C2AR14, CC10, CC5, C6AR5, C2AR2, C1AR12, C1AcF, C2F9, CC1, CC13, CC11, C5AR1	C2AR10, C2AR9, C4AR7, C4AR8, C4AR6, C4AR9, C2AR11, C2AR8, C4AR5, C4AR10, C2AR12, C4AR4, C3AR8, C3AR7, C4AR11, C5AR8
S10	12	C4F3, C1F7, C4AR2, C1F2, C5F1, C4F6, CC11, C4AR1, C1F3, C4F5, C1F1, CC6	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3, C4F3, C5F3	C3AcF, C1AcF, C2AcF, C5F3, C5F4, C5F7, C5F1, C5F2, C5F5, C5F8, C4F6, C5F6	C1F3, C2AcF, C1AcF, C4AR14, C3AR14, C1AR15, C6AR15, CC8, CC2, C6F7, CC14, C1AR9	C5F3, C5F4, C5F2, C5F5, C5F6, C4F2, C1F3, C3F3, C4F6, C4F5, C1F2, C3F2

The proposed feature selection method selected AcF, F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most subjects, which implied that these features were significant for force invariant EMG-PR.

C. TRAINING FOR ONE ORIENTATION WITH A MEDIUM FORCE LEVEL (CASE 2)

To find the performance of the proposed feature selection method for forearm orientation and force invariant EMG-PR, we trained the classifiers for one orientation with a medium force level and tested the classifier for all orientations with all force levels. The orientation and force invariant performances in terms of accuracy, sensitivity, specificity, precision, F1 score, and MCC with standard deviation are shown in Table 2. The summary of results is shown in Fig. 4, where the F1 score is used only for simplicity. In this orientation and force invariant scheme, O2 with a medium force level performed well for training the classifiers. The proposed feature selection method overperformed existing methods in this training arrangement. The proposed feature selection method improved accuracy, sensitivity, specificity, precision, F1 score, and MCC by 4.28%, 12.85%, 2.57%, 10.99%, 13.92%, and 0.15, respectively, when the proposed method was compared with the second-best performing method, chi-square. In this performance evaluation, the proposed feature selection method with the KNN classifier achieved accuracy, sensitivity, specificity, precision, F1 score, and MCC of 92.84%,

TABLE 25. Selected features for training classifiers with O2 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features: Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	14	C2F4, C3F4, C1F1, C5F9, CC13, C3F1, CC2, CC10, C3F9, C3F2, C1AR4, C2F6, C3F5, C3F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3	C1AcF, C1F2, C1F1, C2AcF, C3AcF, C1F3, CC2, C1F7, C1F4, C1F8, C1F5, CC6, C1F9, CC15	C2F3, C3AcF, C2AcF, C1AR14, CC8, C5AR15, C6AR13, C4AR15, CC2, CC9, C3AR14, C2AR13, C3F9, C5F6	C6AR6, C3AR8, C1AR8, C1AR7, C4AR8, C1AR9, C6AR5, C3AR9, C5AR8, C3AR10, C6AR7, C1AR10, C1AR6, C4AR7
S2	17	C3F8, C5F2, C2AR1, C4F6, C6F7, C4AR2, C6AR1, C4F4, C3AR4, C4F3, CC10, C2AR7, C4F7, C2AR13, C3AR15, C2AR15, C2AR10	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3, C4F3, C5F3, C6F3, C1F4, C3F4, C4F4	C2AcF, C1AcF, C3AcF, C3F1, C3F2, C2F1, C3F7, C3F3, C2F2, C4F3, C4F2, C2F3, C2F7, C4F1, C2F5, C4F7, C2F6	C2AcF, C2F1, CC11, C3AR12, C4AR15, C5AR15, CC14, C6F3, C1AR15, C6AR14, C4AR2, CC15, C1F6, C4F6, C1AcF, C5AR8, CC6	C2F6, C5F2, C2F5, C3F3, C2F4, C3F4, C4F2, C3F5, C2F3, C4F3, C3F2, C5F3, C3F6, C6F3, C4F4, C2F2, C6F6
S3	16	C1F2, C3F6, C6F5, C3F7, C1F1, C3F2, CC6, C4F5, C1F7, CC1, C1F3, C3F1, C5F9, C4AR5, C2F6, C1AR12	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3	C2AcF, C1AcF, C3AcF, C1F3, C1F7, C1F1, C1F4, C1F2, C4F2, C2F2, C1F8, C4F1, C1F5, C2F1, C1F9, C4F3	C1F1, C2F3, C6AR13, C4AR15, C3AR14, CC8, CC7, C2AR13, C3F6, C4AR2, C5AR15, C1AcF, C1AR15, CC1, C3AR1, CC2	C1F2, C5F3, C1F3, C5F2, C1F4, C1F5, C5F4, C1F6, C5F5, C5F6, C3F2, C4F6, C4F5, C4F4, C4F3, C2F5
S4	13	C4F1, C1F3, C3F6, C4AR1, C5F7, C1F1, C2F6, C3AR6, C1F6, C4F8, C2F5, C5F2, C1F7	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3	C2AcF, C3AcF, C1AcF, C2F1, C2F2, C2F7, C2F3, C1F2, C1F3, C1F1, C1F7, C3F1, C3F2	C1F2, C3AcF, C2F4, C5AR14, C2AR14, C3AR15, C1AR15, CC7, C4AR15, C3F5, CC5, CC8, C3AR4	C1F3, C1F4, C1F5, C2F2, C1F6, C2F3, C2F4, C3F2, C2F5, C5F3, C2F6, C1F2, C5F2
S5	9	C1F5, C5F2, C2F9, C3F9, C5F4, CC8, C1F6, C5F1, C1F8	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C5F3	C2AcF, C3AcF, C1AcF, C3F2, C3F3, C2F1, C3F1, C5F3, C3F4	C1F4, C2AcF, CC10, CC7, C2AR13, C3AR14, C4AR15, C5AR15, C1AR15	C6AR8, C6AR7, C6AR9, C6AR6, C3AR7, C3AR6, C6AR5, C3F3, C3F6
S6	13	C4F7, C2F2, C1F3, C2F1, C4F9, C1F5, CC3, C4F5, C2F7, C6F1, C4F1, C1F6, C1F2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C1F3, C2F3, C3F3	C2AcF, C1AcF, C3AcF, C4F1, C4F2, C4F7, C4F8, C4F3, C2F1, C4F4, C3F1, C3F2, C4F9	C4F3, C6AR3, C3AR11, C6AR15, C1AR15, C3AR15, C2AR12, CC4, C1F8, C5AR15, CC3, C4AR14, C2F1	C4F3, C4F2, C3F2, C2F3, C4F4, C2F4, C3F3, C2F2, C2F5, C2F6, C4F5, C3F4, C1F6
S7	11	C4F4, C3F2, C3AR9, C4F1, C4AR3, C1F2, C5AR7, C3F1, C3F3, C4AR7, C4AR13	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3	C2AcF, C1AcF, C3F1, C3F7, C3F2, C3F8, C4F1, C3F9, C4F2, C3F3, C3F4	C4F4, C3AcF, C4AR12, C2AR11, CC4, C6AR15, C5AR15, C1AR15, C3F2, C3AR12, C5F6	C3F3, C3F4, C3F6, C3F5, C3F2, C4F6, C4F5, C4F4, C4F3, C5F3, C5F4
S8	7	C1F2, C3F2, C4F2, C2F2, C2AR7, C4F1, C3F3	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C2AcF, C1AcF, C1F2, C2F1, C3AcF, C2F2, C1F1	C1F2, C3AcF, C6AR14, C3AR15, C4AR15, C1AR15, C2AR10	C3F3, C1F3, C1F4, C1F5, C3F4, C1F6, C1F2
S9	6	C5F9, C3F3, C1F2, C2F3, C3AR3, C1AR1	C1F1, C2F1, C3F1, C5F1, C6F1, C1F2	C2AcF, C1AcF, C2F9, C2F8, C2F7, C3AcF	C5F4, C1F3, C1AcF, C6AR9, C4AR15, C2AR15	C1F3, C1F2, C1F4, C2F6, C5F4, C5F2
S10	5	C1F7, C1AcF, C3F8, C1F4, C1F2	C1F1, C2F1, C3F1, C4F1, C5F1	C3AcF, C1AcF, C2AcF, C2F3, C2F2	C1F3, C2AcF, C2F7, C3AR14, C1AR15	C1F4, C1F5, C1F3, C1F6, C2F2

78.52%, 95.70%, 80.35%, 78.44%, and 0.75, respectively employing 5 to 17 features only (Table 25). The proposed feature selection method selected F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most subjects. In addition, we performed two-way ANOVA considering independent variables, classifiers, and feature selection methods (Table 8 and Table 9). The obtained p-values indicated that the F1 score significantly depended on the feature selection methods ($p \ll 0.001$) rather than the classifiers ($p=0.26$). Also, we obtained much smaller p-values ($p \ll 0.001$) when the proposed feature selection method was compared with each of the existing feature selection methods, which confirmed the significant performance improvement of the proposed feature selection method.

D. TRAINING FOR TWO ORIENTATIONS WITH A MEDIUM FORCE LEVEL (CASE 3)

To achieve satisfactory EMG-PR performance for forearm orientation and force invariant EMG-PR, we trained the classifiers for two orientations with a medium force level and tested the classifiers for all orientations with all force levels. The detailed EMG-PR performances with standard deviation are shown in Table 3. The performances are also shown in Fig. 5 using F1 scores only. In this training scheme, the proposed feature selection method achieved the highest performance training KNN classifier for both O1 and O3 with a medium force level. The obtained F1 score was satisfactory and about 13% higher than case 2. In this study, the proposed feature selection method improved accuracy,

TABLE 26. Selected features for training classifiers with O3 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	20	C3F7, C2F7, CC2, C3F5, C1AR10, CC13, C5F1, C4F8, C3F2, C5F9, C4AR12, C3F1, C1F3, CC11, C2F1, C1AR15, C3F6, C3AR12, C2F2, C3F9	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4, C3F4, C4F4, C5F4	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F3, C1F7, CC2, C1F4, C5F8, C5F1, C5F7, CC13, C5F4, C1F8, C5F3, C5F2, C6F2, C5F9, C6F1	C2F7, C3AcF, C1AR14, CC4, C4AR15, CC8, C3AR15, C5AR15, C6AR14, CC14, CC9, CC1, C3AR4, C2AR15, C4AR4, C1F8, CC3, C5AR2, CC13, C1AR4	C6AR9, C5AR7, C5AR8, C6AR10, C5AR6, C6AR8, C4AR9, C5AR9, C6AR11, C5AR5, C4AR8, C1AR10, C6AR7, C4AR10, C5AR10, C6AR12, C1AR11, C5AR4, C1AR9, C3AR11
S2	13	C4F4, C4F3, C4F7, C4F6, C3F1, C4F5, CC15, C2AcF, C1F5, C4F9, CC11, C5F6, C4F8	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3	C1AcF, C2AcF, C3AcF, C2F1, C2F2, CC14, C2F7, C6F2, C2F8, C6F1, C2F3, C2F9, C4F1	C4F4, C2AcF, C1AR2, CC7, C1AR15, C6AR15, C2AR14, C2F8, C5AR14, C4AR15, CC6, C6F4, C6AR2	C3F2, C3F3, C3F6, C3F4, C3F5, C4F4, C4F3, C4F5, C2F5, C2F6, C4F6, C6F6, C2F4
S3	10	C1F2, C6F6, C1AR5, C4F1, C4AR1, CC4, C4F8, C2AR1, C1AR1, CC6	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C3AcF, C1F4, C1F3, C1F7, C1F8, C1AcF, C1F5, C1F9, C1F6	C1F1, C2F3, C6AR1, C6AR15, C4AR15, C2AR15, C3F8, C4AR2, CC7, CC8	C1F3, C1F2, C1F4, C1F5, C1F6, C2F6, C2F5, C4F3, C2F4, C4F2
S4	16	C4F2, C1F2, C3F4, C5F2, C1F8, C4AR4, CC3, C3F6, C1F7, C3F9, C1F3, C5F1, C1F4, C1F1, C5F7, C1F9	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3	C1AcF, C3AcF, C2AcF, C3F1, C2F2, C1F3, C3F2, C2F1, C1F7, C1F1, C1F2, C3F3, CC10, C3F7, C3F4, C5F3	C3F1, CC9, C3AR15, C5AR15, C4AR15, C1AR15, C2F2, C6F4, CC5, C1AcF, C2AR3, C1F1, CC8, C3AcF, C4F3, C5F2	C1F3, C5F3, C4F2, C1F4, C5F4, C2F2, C4F3, C1F2, C5F5, C3F2, C1F5, C3F3, C2F3, C5F6, C3F4, C5F2
S5	6	C1F5, C3F5, C5F2, C6F7, C2F8, C1F8	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2	C3AcF, C2AcF, C1AcF, C2F1, C2F2, C5F3	C1F3, CC3, C4AR7, CC7, C2AR14, C3AR14	C5AR6, C6AR9, C1F4, C1F5, C1F6, C5AR5
S6	7	C4F8, C2F1, C1F6, C3F8, C1F4, CC10, C2AR1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C2AcF, C3AcF, C1AcF, C4F2, C4F1, C3F5, C3F4	C4F8, C3F2, C2AR2, C1AR11, C6AR15, C4AR15, C5AR15	C1AR8, C1AR7, C1AR9, C1AR6, C1AR10, C5AR10, C1AR5
S7	8	C4F6, C3F1, C6F9, C6F8, C6F6, C4F5, C6F7, C4AR13	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C2AcF, C3AcF, C1AcF, C4F1, C4F2, C4F3, C4F7, C4F4	C4F9, C3AcF, C3AR1, CC4, C4AR14, C2AR14, C6AR15, C5AR15	C4F4, C4F5, C4F3, C4F6, C4F2, C3F3, C3F4, C3F5
S8	10	C4F1, C3F2, C2F5, C1F2, C6F6, C2F3, C2F1, C3F1, CC14, C2F6	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C1AcF, C1F7, C1F8, C2AcF, C1F9, C3AcF, CC11, C1F5, C1F4, C1F3	C1F2, C2AcF, C5AR9, C3AR14, C2AR14, CC14, C2F7, CC9, CC11, C6F5	C4F3, C4F4, C4F5, C4F6, C4F2, C3F4, C3F3, C3F5, C3F6, C3F2
S9	9	C2F4, C5F7, C2F1, CC9, C3F2, C1F9, C5F8, CC4, C2F2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C2AcF, C3AcF, C1AcF, C1F1, C1F2, C1F7, C1F8, C4F1, C1F3	C5F4, C1F3, C3AcF, C4AR14, C6AR15, CC5, C2AR14, C4F7, C3AR13	C4F2, C4F3, C4F4, C4F5, C4F6, C1F2, C2F4, C2F5, C2F3
S10	9	C4F6, C3F1, C6F4, C1F7, C3F2, C4F5, C2F1, C4F9, C4AR15	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3	C3AcF, C1AcF, C2AcF, C1F7, C1F6, C1F8, C1F5, C1F4, C1F9	C1F2, C2AcF, CC11, C2AR10, C6AR15, C2F6, CC15, C3F9, C1AR14	C1F2, C1F3, C3AcF, C5F2, C5F6, C2F2, C3F2, C5F5, C3F3

sensitivity, specificity, precision, F1 score, and MCC by 3.82%, 11.45%, 2.29%, 9.86%, 11.43%, and 0.13, respectively, when the proposed method was compared with chi-square. The proposed feature selection method with the KNN classifier achieved accuracy, sensitivity, specificity, precision, F1 score, and MCC of 97.19%, 91.57%, 98.31%, 92.14%, 91.46%, and 0.90, respectively, employing 7 to 20 features only (Table 28). The proposed feature selection method selected F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most subjects. Again, we evaluated p-values considering independent parameters, classifiers, and feature selection methods (Table 10 and Table 11). The obtained p-values indicated that the F1 score significantly depended on the feature selection methods ($p \ll 0.001$) rather than the classifiers ($p=0.051$). Also, the F1 score obtained by the proposed feature selection method and each of the existing feature selection methods were significantly different since p-values were much smaller than 0.001.

E. TRAINING FOR ALL ORIENTATIONS WITH A MEDIUM FORCE LEVEL (CASE 4)

In this study, we trained the classifiers for all orientations with a medium force level and tested the classifiers for all orientations with all force levels. The detailed EMG-PR performances with standard deviation are shown in Table 4. The summary of the performances is also shown in Fig. 6 using F1 scores only. The proposed feature selection method achieved the highest performance with the KNN classifier in this

TABLE 27. Selected features for training classifiers with O1 and O2 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	19	C5F2, C1AcF, C3F6, C1F5, C3AcF, CC13, CC2, C5F1, C3F9, C3F5, C5F8, C2AR3, C1AR6, C6AR15, C5AR10, C3F3, C5F7, C3F8, C3F4	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4, C3F4, C4F4	C1AcF, C3AcF, C1F1, C1F2, C1F7, C1F4, C1F3, C1F8, C1F5, C1F9, C1F6, C2AcF, CC2, C5F2, CC6, CC14, CC15, C5F1, CC13	C1AcF, C2F7, C1AR12, CC5, C3AR15, C2AR15, C5AR14, C6F3, C6AR14, C4AR15, CC2, C5AR1, C3AR2, CC9, C3AcF, C1AR1, CC11, CC10, CC13	C1F3, C1F4, C1F2, C1F5, C1F6, C5F3, C5F4, C5F5, C5F6, C5F2, C4F3, C4F4, C4F2, C4F5, C4F6, C1F7, C1F1, C1F8, C1F9
S2	5	C3AcF, C4F9, C1F2, C6F9, C1F7	C2F1, C3F1, C4F1, C5F1, C6F1	C2AcF, C1AcF, C3AcF, C3F1, C3F2	C3AcF, C1F7, C1AR2, CC11, C5AR15	C2AR7, C1AR7, C5AR7, C4AR7, C1AR5
S3	13	C1F2, C3F2, C6F7, C4F4, C1F4, CC2, C1F3, C3F7, C5F9, C3AR10, CC3, C3F3, CC6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3	C2AcF, C1AcF, C3AcF, C1F3, C1F1, C1F2, C1F4, C1F7, C4F2, C1F8, C4F1, C1F5, C1F9	C1F1, C2F3, C6AR13, C3AR14, C5AR15, CC8, CC11, C4AR14, C2AR13, C3F7, CC1, C1F4, CC7	C5AR8, C5AR7, C1F4, C1F3, C4F3, C4F4, C1F5, C4F5, C4F6, C1F6, C4F2, C3F4, C3F3
S4	7	C4F2, C3AcF, C1F3, C2F7, C1F1, C2F4, CC3	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C2AcF, C3AcF, C1AcF, C2F2, C2F1, C2F3, C2F7	C1F2, C2F3, CC9, C6AR15, C2AR14, C3AR14, C5AR13	C1F3, C2F2, C2F3, C1F4, C2F4, C2F5, C2F6
S5	8	C1F5, C5F2, C3F5, C3AcF, C6F6, C2F9, C4F1, C1F4	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3	C2AcF, C3AcF, C1AcF, C3F2, C3F3, C3F1, C2F1, C3F4	C1F4, C1AcF, CC5, CC7, C4AR15, C5AR15, C6AR14, C1AR15	C5F2, C1F3, C5F3, C1F2, C5F4, C3F2, C3F3, C1F4
S6	7	C4F5, C2F1, C1F9, C3F2, C3AcF, C4F4, C1F6	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2, C2F2	C3AcF, C2AcF, C1AcF, C4F1, C4F2, C4F7, C4F3	C4F4, C3AR3, CC14, C2AR12, C3AR14, C4AR15, C1AR15	C4AR6, C4AR5, C6AR7, C3AR9, C4AR7, C4AR10, C4F2
S7	14	C1F3, C3F2, C4AR5, C4F5, C3F8, C1AR9, C3F1, C4F4, C3F7, C4AR1, C4AR3, C3AR12, C3F9, C4F1	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3	C1AcF, C2AcF, C3F1, C3F7, C3F2, C3F8, C3F3, C3F9, C3F4, C5F4, C5F3, C3F5, C3F6, C5F7	C4F9, C3AR1, C4AR14, C2AR13, CC4, C1AR15, C6AR15, C3F1, C1AR4, C5AR14, C5F8, CC2, C4AR3, CC7	C4F4, C4F3, C4F5, C4F6, C4F2, C3F6, C3F3, C3F5, C3F4, C3F2, C1F2, C1F3, C1F4, C1F5
S8	14	C3F9, C2F6, C6F8, C4F1, C5AR1, C2AR7, C1F6, C2F7, C6F1, C2AR1, C4F2, C3F7, C1AR12, C3F6	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3	C2AcF, C3AcF, C2F1, C2F2, C6F8, C6F4, C6F2, C6F1, C6F5, C6F9, C6F6, C6F7, C6F3, C1F2	C1F2, C2AcF, C6AR1, C1AR14, C4AR14, C2AR15, C3AR15, CC14, C2AR4, CC4, C2F7, C6F2, CC8, C4AR2	C3F4, C3F5, C3F3, C3F6, C2F2, C2F4, C2F3, C2F5, C2F6, C3F2, C4F3, C4F4, C4F2, C4F5
S9	16	C5F5, C2F7, C1F1, C2AR1, C3F2, C2F2, C1F8, CC10, C1F3, C1AR7, C2F6, C1F7, C2F4, C6AR9, C2F3, C2F9	C1F1, C2F1, C3F1, C5F1, C6F1, C1F2, C2F2, C3F2, C5F2, C6F2, C1F3, C2F3, C3F3, C5F3, C6F3, C1F4	C2AcF, C1AcF, C2F9, C3AcF, C2F8, C2F7, C2F1, C2F3, C2F4, C2F5, C2F6, C2F2, C6F2, C6F1, C4F2, C1F1	C5F4, C1F1, C1AcF, C6AR14, C4AR14, C3AR14, C2AR14, CC5, CC11, C4F1, C1AR14, CC1, C2F6, C1AR1, C5F2, C1F9	C5AR6, C3AR7, C2AR7, C3AR6, C5AR5, C2AR10, C2AR9, C5AR7, C1AR6, C1AR7, C2AR6, C3AR5, C5F2, C3AR8, C1F2, C5F3
S10	12	C1F7, C1AcF, C4F6, C6F8, C2F5, C1F8, C3F2, C1F4, C4F9, C2F1, C1F9, C5AR1	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3	C1AcF, C3AcF, C2AcF, C4F6, C4F5, C4F9, C4F4, C5F4, C5F3, C5F5, C3F1, C4F8	C1F7, C1AcF, C6AR13, C1AR15, CC8, C5AR15, C2AR14, C3AR15, C4AR14, C6F6, CC5, CC11	C4F6, C4F5, C5F3, C5F4, C4F4, C5F5, C5F2, C5F6, C3F3, C3F4, C4F3, C1F3

training scheme. The obtained F1 score was 1.81% higher than in case 3. However, the proposed feature selection method improved accuracy, sensitivity, specificity, precision, F1 score, and MCC by 3.35%, 9.14%, 1.83%, 8.67%, 9.22%, and 0.11 respectively, when the proposed method was compared with ReliefF. In this training scheme, the proposed feature selection method with the KNN classifier achieved accuracy, sensitivity, specificity, precision, F1 score, and MCC of 97.77%, 93.31%, 98.66%, 93.53%, 93.27%, and 0.92, respectively employing 7 to 19 features only (Table 30). The proposed feature selection method selected AcF, F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most of the subjects.

Again, we evaluated p-values considering independent parameters, classifiers, and feature selection methods (Table 12, Table 13, and Table 14). The obtained p-values indicated that the F1 score significantly depended on both the feature selection methods ($p \ll 0.001$) and the classifiers ($p=0.012$). Also, the F1 score obtained by the proposed feature selection method and each of the existing feature selection methods were significantly different since p-values were much smaller than 0.001. Besides, the KNN classifier provided significantly improved performance than LDA ($p=0.037$), but the SVM classifier provided an almost equal F1 score to the KNN classifier ($p=1$).

TABLE 28. Selected features for training classifiers with O1 and O3 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	19	C3F2, C5F2, CC13, C6F2, C1F4, CC10, C3F4, C3F3, C2F9, C3F7, C3F1, C5AR9, C3F6, C3F8, CC2, C2F2, C1F5, C2F7, C3F5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3, C1F4, C2F4, C3F4, C4F4	C1AcF, C3AcF, C2AcF, C1F1, C1F2, C1F7, C1F3, C1F8, C1F4, C1F9, C1F5, C6F2, C1F6, CC13, C4F2, C6F1, C4F1, C5F1, C5F2	C2F9, C1AcF, C1AR13, CC4, C4AR15, C2AR15, C3AR15, C5AR15, C6AR14, C5AR6, C6F2, CC3, CC9, C3AR7, CC6, CC7, CC1, CC10, C1AR1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4
S2	7	C2AcF, C4F9, C6F9, C2F9, C3F1, C3AR1, C3AR2	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C3AcF, C2AcF, C1AcF, C4F2, C4F1, C2F1, C4F3	C4F4, C1AcF, CC11, C6AR14, C2AR14, C5AR14, C1AR14	C5F5, C5F4, C5F6, C5F3, C5F2, C4F3, C4F2
S3	11	C1F4, C3F8, C2AcF, C5F6, C1F1, C3F1, C2F1, C2AR3, C4AR5, C1F2, CC5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3	C2AcF, C3AcF, C1F4, C1F7, C1F3, C1F8, C1F5, C1F9, C1F6, C1F1, C1F2	C1F1, C2F2, C3AR13, C2AR15, C6AR15, C1AR15, C4AR1, C2AR4, CC8, C3F7, CC7	C1F4, C1F5, C1F3, C1F6, C1F2, C4F5, C4F6, C4F4, C3F2, C4F3, C3F3
S4	9	C4F2, C2F2, C3F6, C1F3, C5F3, C4F4, C4F9, C5F7, C4F6	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2	C1AcF, C3AcF, C2AcF, C2F2, CC10, C2F1, C2F3, C1F3, C1F7	C3F1, C5F2, C6AR15, C3AR15, C4AR15, C2F8, C2AR14, CC5, CC15	C6AR7, C1AR7, C3AR6, C6AR8, C4AR9, C2AR4, C4AR11, C2F6, C2F5
S5	8	C5F4, C3F5, C1F9, C2AcF, C4F4, C6F6, C5F8, C5F5	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3	C3AcF, C2AcF, C1AcF, C1F2, C1F7, C1F1, C1F3, C2F1	C1F3, C1AR1, CC7, C3AR15, C4AR15, C4AR1, C3AR7, C1AcF	C1AR7, C1AR8, C1AR6, C1AR9, C1AR5, C1AR10, C1AR4, C5AR6
S6	17	C4F3, C2F1, C1F3, C3F5, CC3, C2AR1, C1F5, C4F9, C1F9, CC10, C5F2, C4F6, C6F3, C4F5, C4F8, C2AR7, C1F6	C1F1, C2F1, C3F1, C4F1, C6F1, C1F2, C2F2, C3F2, C4F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4	C2AcF, C3AcF, C1AcF, C3F5, C3F6, C3F4, C3F8, C3F9, C4F2, C3F3, C2F1, C3F7, C4F1, C2F7, C4F3, C4F7, C4F4	C4F4, C3F1, C2AR11, C1AR13, C5AR15, C4AR15, C3AR15, C1AcF, CC4, CC9, C6AR14, C1F7, CC14, C3AR11, CC5, C2F1, C6AR1	C3F3, C3F4, C3F5, C3F2, C3F6, C2F2, C4F2, C2F3, C4F3, C1F4, C4F4, C2F4, C1F5, C1F6, C2F6, C2F5, C4F5
S7	15	C4F4, C3F9, C6F6, C1AR3, C1F2, C4F1, C5F3, C2AR8, C4AR6, C6AR10, C1F7, CC15, C2AR5, C1F1, C5AR15	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C3F3, C4F3, C5F3	C2AcF, C1AcF, C3AcF, C4F2, C4F1, C3F7, C4F3, C3F8, C3F1, C3F9, C4F7, C3F4, C3F3, C3F5, C3F6	C4F6, C3AR2, C6AR13, CC4, C2AR14, C5AR15, C4AR14, C1AR14, C3F1, C5F2, C4AR3, C2AR9, CC2, C6F6, CC7	C1AR8, C4AR6, C3AR8, C6AR11, C4AR5, C6AR7, C6AR8, C1AR6, C4F4, C4F5, C1AR7, C4F3, C3F5, C3F6, C4F6
S8	20	C3F3, C2F6, C1F6, CC14, C2F1, C2F9, C3F8, CC10, C2AR3, CC8, C3F2, C6F9, C4F2, C4AR10, CC2, CC9, C3F1, C3AR15, C4AR14, C3F9	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4, C2F4	C3AcF, C2AcF, C1F8, C1F7, C1F9, C1F4, C1F5, C1F3, C1F6, CC11, C6F2, C6F1, C1F2, C1F1, CC14, CC4, C6F3, C1AcF, C6F7, C4F3	C3F8, C1AcF, C5AR11, C2AR14, C3AR14, CC12, C1AR13, C6F6, CC1, CC10, C2AR1, C3AR1, C2F8, CC3, C1F1, C4AR13, CC9, C4F2, C6F7, C2F1	C2F4, C2F6, C2F5, C2F3, C2F2, C3F3, C4F5, C4F6, C4F4, C6F5, C6F6, C6F2, C6F4, C6F3, C3F2, C3F4, C4F3, C3F5, C3F6, C1F5
S9	14	C5F4, C2F2, C6F2, C5F6, C1F6, C2F9, C4F4, C2F6, C5F5, C4AR12, C2F8, C5F9, C2F1, C2AR12	C1F1, C2F1, C3F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3	C3AcF, C2AcF, C1AcF, C1F1, C1F7, C2F9, C2F8, C1F2, C1F8, C2F7, C1F9, C1F3, C2F3, C2F4	C5F4, C1F3, C4AR14, C6AR14, CC5, C2AR14, C4F4, CC1, C2F6, C3AR13, C5F1, CC4, C1AR14, CC3	C1AR8, C4AR10, C5AR9, C3AR8, C4AR8, C5AR8, C5AR7, C3AR7, C2AR7, C2AR9, C4AR6, C1AR6, C3AR6, C5AR6
S10	15	C4F6, C5F3, C1F4, C2F1, C4F9, C3F4, CC1, C2F9, C6F1, C1F6, C1F5, C5F4, C4F4, C2F2, C1F8	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2, C5F2, C1F3, C3F3, C4F3, C5F3, C1F4, C3F4, C4F4	C1AcF, C3AcF, C2AcF, C5F3, C5F2, C5F1, C5F7, C1F5, C1F4, C5F4, C1F6, C4F6, C1F3, C4F5, C5F5	C1F3, C1AcF, C4AR3, C2AR12, C6AR15, CC4, C6F4, CC1, C3F9, C1AR15, C5AR14, C1AR3, CC15, C4F9, CC8	C4F6, C4F5, C4F4, C4F3, C1F3, C3F4, C3F3, C3F5, C1F4, C3F6, C5F3, C1F5, C5F4, C5F6, C5F5

F. PERFORMANCE COMPARISON

To compare and validate the proposed feature selection method for resolving forearm orientation and muscle force variation, we considered most related existing works shown in Table 5. In this table, some additional works that deal with muscle force variation were included since only two related works were found to the best of our knowledge. The table shows that the proposed feature selection method achieved 2.92% and 2.27% improved F1 scores compared to Rajapriya *et al.* [19] and Khushaba *et al.* [20], respectively, where three orientations were employed for training. In addition to training with all orientations, the proposed feature selection method achieved an improved F1 score of 91.46% training with O1 and O3 only. This study also noted that

TABLE 29. Selected features for training classifiers with O2 and O3 with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	15	C2F3, C3F7, CC15, C1F3, C5F8, C6AR6, C2F1, C2F7, CC2, C2F2, C3F1, C2F5, C3F3, C5F3, C1AR10	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2, C5F2, C1F3, C2F3, C3F3, C4F3, C5F3	C1AcF, C2AcF, C1F2, C1F1, C3AcF, CC2, C1F3, C1F7, C5F7, C5F8, C5F3, C5F1, C5F4, CC15, CC6	C2F3, C4F2, C6AR1, C6AR14, C1AR15, CC5, C5AR15, CC8, CC2, C3AR15, C1AR5, C3AR6, CC13, CC10, C4AR15	C5F2, C5F3, C5F4, C4F6, C4F5, C4F2, C4F4, C1F3, C4F3, C1F2, C5F5, C1F4, C5F6, C1F5, C1F6
S2	6	C3AcF, C6F8, C1F5, C1F2, C1F1, C1F3	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2	C1AcF, C2AcF, C3AcF, C2F1, C2F2, C2F7	C4F3, C3AcF, CC11, C6AR15, C1AR14, C5AR15	C4F6, C4F5, C4F4, C3F2, C4F3, C6F3
S3	10	C1F2, C3F8, C2AcF, C6F5, C3F1, C1F1, C4AR4, C2F1, C1F3, CC8	C1F1, C3F1, C4F1, C5F1, C6F1, C1F2, C3F2, C4F2, C5F2, C1F3	C2AcF, C3AcF, C1AcF, C1F4, C1F5, C1F8, C1F9, C1F3, C1F7, C1F6	C1F1, C2F3, C6AR7, C1AR15, C4AR14, CC5, C2AR13, CC4, C3F5, C4AR1	C1F3, C1F2, C1F4, C5F2, C5F3, C5F4, C5F6, C5F5, C1F5, C3F2
S4	11	C4F3, C1F2, C5F7, C3F6, C1F7, C6F1, C5F6, C3AR7, C4F2, C4F8, C1F3	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2	C3AcF, C1AcF, C2AcF, CC10, C1F3, C5F3, C1F7, C1F1, C1F2, C3F2, C3F1	C1F2, C6F7, C5AR5, C3AR15, C4AR15, C5AR15, C1AR15, CC10, CC11, C2AcF, C1AcF	C5F3, C5F4, C3F3, C3F4, C1F3, C1F2, C3F2, C5F5, C3F5, C3F6, C5F2
S5	9	C1F6, C3F4, C5F7, C2F7, C6F1, C1F9, C5F1, C5F3, C3F8	C1F1, C3F1, C5F1, C1F2, C3F2, C5F2, C1F3, C3F3, C5F3	C3AcF, C2AcF, C1AcF, C5F3, C5F4, C2F1, C5F7, C5F8, C2F2	C1F4, C3F5, C3AR8, CC14, CC7, C2AR13, C1AR15, C5AR14, C1AR3	C3F5, C3F4, C3F6, C3F3, C3F2, C1F3, C1F4, C1F5, C1F6
S6	9	C4F7, C3F9, C1F5, C2F1, C6F6, C4F1, C4F2, C3F1, C4F9	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2	C2AcF, C3AcF, C1AcF, C4F1, C4F2, C3F1, C3F2, C3F3, C3F7	C4F8, C3F3, C2AR3, C1AR13, C6AR15, C4AR15, C3AR15, C4AR3, C3AR10	C3F3, C3F2, C3F4, C3F5, C3F6, C4F3, C4F2, C4F4, C4F5
S7	9	C4F3, C3F2, C5F9, C4F1, C6F8, C4F4, C5F8, C4F2, C4F5	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2, C4F2	C1AcF, C2AcF, C3AcF, C4F1, C4F2, C5F3, C5F7, C4F3, C4F7	C4F8, C3AcF, C2F9, C3AR14, CC4, C6AR15, C1AR15, C5AR15, C4AR12	C3F3, C3F2, C3F4, C3F5, C3F6, C4F2, C4F3, C5F3, C4F4
S8	8	C1F2, C4F2, C2F1, C3F4, C2F5, CC8, C3F1, C1F9	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2, C3F2	C1AcF, C2AcF, CC11, C3F1, C3F2, C6F4, C6F5, C6F3	C1F2, C2AcF, C6AR12, C4AR14, C3AR15, C2AR14, C3AR6, CC6	C4F5, C4F4, C4F6, C4F3, C2F5, C2F6, C2F4, C3F2
S9	7	C5F6, C2F1, C3F4, C1AR1, C5F9, C3F3, C1AR5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C2AcF, C1AcF, C3AcF, C4F3, C4F4, C4F1, C4F7	C5F8, C1F3, C1AcF, C6AR13, CC5, C4AR14, C2AR14	C5F4, C5F5, C5F3, C5F6, C5F2, C1F3, C1F2
S10	7	C4F4, C3F9, C5F3, C6F1, C4F6, C3F5, C2F3	C1F1, C3F1, C4F1, C5F1, C1F2, C3F2, C4F2	C3AcF, C1AcF, C2AcF, C1F5, C1F6, C1F4, C1F8	C2AcF, C1F7, C6F6, C5AR14, C1AR15, C2AR15, CC1	C1F3, C1F4, C1F5, C5F3, C1F6, C5F4, C5F5

the proposed work achieved these improved performances using the least number of features of 7 to 20 (Table 28 and Table 30). Thus, the proposed work showed its robustness to reduce data dimensionality of feature space, design complexity, and computational power of the hardware as defined in [19]. Again, the performances achieved in this work were higher than the other works shown in this table, where only muscle force variation was resolved. So, the proposed feature selection method would be an option to resolve both the forearm orientation and muscle force variation problems of EMG-PR.

IV. DISCUSSION

Myoelectric pattern recognition is an efficient method to decode the intended movements and restore the missing functionalities of an amputee [42], [44]. Nevertheless, several factors affect the EMG-PR performance [45], [46]. These factors change the time-domain and frequency-domain characteristics of the EMG signal and alter the values of existing features extracted from the EMG signal. Consequently, the factors degrade the EMG-PR performance [14], [19], [23]. Researchers have proposed different feature extraction methods to resolve these factors, including multiple numbers of features. The feature space becomes very high when extracting these features from a multichannel EMG signal [47]. In addition to high dimensionality, the EMG features are problem-specific, i.e., a feature extraction method or a group of features proposed to resolve any particular problem may not be effective for other problems [21], [47]. So, to resolve any single or multiple limiting factors of EMG-PR, an efficient feature selection method is required to find out the least number of features.

We have proposed an efficient feature extraction method to resolve forearm orientation and muscle force variation simultaneously. The proposed feature selection method considered a feature extracted from each channel as a distinct feature. Thus, the proposed feature selection method selected the features and the channels. In addition, the proposed feature

TABLE 30. Selected features for training classifiers with all orientations with a medium force level and testing with all orientations with all force levels.

Subjects	No. of Features	Selected Features				
		Proposed	Chi-Square	ReliefF	MRMR	NCA
S1	14	C3F2, C5F2, C1F3, C3AcF, C1AcF, C3F5, C2F8, C2AcF, CC2, C3F9, C3F7, C2F9, CC13, C3F1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3	C1AcF, C2AcF, C3AcF, C1F1, C1F2, C1F3, C1F7, C1F4, C1F8, CC2, C1F9, C1F5, CC6, C1F6	C2F3, C1AcF, C1AR14, CC8, CC4, C6AR15, C4AR15, CC9, C3AR15, C1AR2, C5AR15, CC2, C3AR6, C5AR1	C1F2, C1F3, C5F2, C1AcF, C1F4, C5F3, C4F2, C1F5, C4F3, C4F6, C5F4, C1F1, C1F6, C3AcF
S2	8	C2AcF, C4F3, C1AcF, C1F6, C3F1, C3AcF, C2F9, CC8	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2	C2AcF, C1AcF, C3AcF, C3F1, C3F2, C2F1, C4F2, C4F1	C2AcF, C3F3, C5AR14, CC4, C1AR15, C4AR15, CC1, C6F1	C3F2, C2F2, C2AcF, C4F4, C4F3, C4F5, C3F3, C2F3
S3	10	C2AcF, C1F1, C3F7, C2F8, C4F7, C5F1, C1F3, C5F6, CC2, C3AcF	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C2AcF, C3AcF, C1AcF, C1F3, C1F7, C1F1, C1F4, C1F2, C1F8, C1F5	C1F1, C2F3, C6AR7, C5AR15, C4AR15, C1AR15, C2AR13, C3AR10, C3F4, CC7	C1F2, C1F3, C2AcF, C1F4, C3AcF, C4F2, C1F5, C6F6, C1F6, C6F5
S4	10	C4F2, C3AcF, C2F2, C1F1, C3F9, C1AcF, C2AcF, C5F3, C4F5, C4F3	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2	C3AcF, C1AcF, C2AcF, C2F2, C2F1, CC10, C1F2, C1F1, C3F1, C2F3	C1F2, C3AcF, C2AR14, C5AR14, CC8, C3AR15, C4F9, C4AR15, CC10, C4AR1	C3AcF, C1F3, C2F2, C5F3, C1F2, C2AcF, C4F2, C5F2, C3F2, C2F3
S5	13	C1F4, C3F3, C5F7, C2AcF, C2F1, C3AcF, C1F2, C6F1, C1F9, C1AcF, C3F5, C1F8, C3F2	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3	C2AcF, C3AcF, C1AcF, C2F1, C3F2, C3F3, C3F1, C2F2, C1F2, C3F4, C5F3, C3F5, C5F7	C1F4, C1AR1, C4AR13, CC7, C2AR13, C3AR14, C2F7, C5F1, C3F4, C1AcF, CC10, C4F8, CC4	C2AcF, C3AcF, C1F2, C1F3, C1F4, C1F5, C5F2, C3F2, C5F4, C1F6, C3F6, C5F5, C2F2
S6	12	C4F7, C2F1, C3F7, C1F8, C6F3, C5F9, C4F1, C2AcF, C1AcF, C6F6, C5F8, C6F1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2	C2AcF, C3AcF, C1AcF, C4F1, C4F2, C4F7, C4F3, C4F8, C2F1, C3F3, C3F4, C3F5	C4F8, C3AcF, C2AR3, C1AR13, C4AR15, C5AR15, C3AR13, C6AR15, CC4, CC3, C6AR2, C1AcF	C3AR7, C4AR5, C5AR8, C4AR6, C3AR8, C1AR7, C5AR7, C3AR9, C4F2, C3F3, C4F3, C3F4
S7	7	C4F4, C3F2, C3AcF, C5F3, C4F1, C1F4, C3F5	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2	C2AcF, C1AcF, C3AcF, C3F1, C3F7, C4F1, C4F2	C4F5, C3AR1, CC4, C4AR14, C6AR15, C2AR14, C1AR15	C4F6, C4F5, C4F4, C4F2, C4F3, C3F3, C3F2
S8	19	C1F2, C3AcF, C4F1, C3F3, C1AcF, C2AR11, C4F2, C1F6, C4F7, C2F2, C1F9, C4F8, C1F1, C1F5, C2AR15, C3F2, C1F4, CC11, C3F1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3, C3F3, C4F3, C5F3, C6F3, C1F4	C2AcF, C3AcF, C1AcF, C1F3, C1F2, C1F7, C1F1, C1F4, C1F8, C6F2, C1F5, C6F1, C2F1, C1F9, C1F6, C2F2, CC11, C6F3, C6F7	C1F2, C2AcF, C6AR13, C2AR15, C4AR15, C3AR15, C1AR15, C3AR1, CC2, C2AR2, C6F5, CC3, CC14, C2F6, CC6, C4AR4, C1F9, C3F2, CC12	C4F2, C6F6, C4F4, C4F3, C2F4, C2F5, C6F2, C2F6, C6F5, C2F2, C2F3, C6F4, C4F5, C6F3, C1F3, C4F6, C1F4, C1F5, C3F5
S9	14	C5F5, C2F7, C3F2, C2AcF, C1F8, C4F4, C6AR12, C1AcF, C1AR13, C2F3, CC10, C2F5, C5AR1, C2F1	C1F1, C2F1, C3F1, C4F1, C5F1, C6F1, C1F2, C2F2, C3F2, C4F2, C5F2, C6F2, C1F3, C2F3	C2AcF, C1AcF, C3AcF, C2F9, C2F8, C2F7, C1F1, C2F1, C2F3, C2F6, C2F5, C2F4, C2F2, C1F2	C5F4, C1F3, C4AR15, C3AR15, C6AR15, CC5, C2AR14, C3AcF, CC11, C2AR1, C4AR1, CC6, C6F1, C2F6	C2F3, C5F2, C2F4, C5F3, C2F2, C2F5, C5F4, C2F6, C5F5, C5F6, C1F3, C1F4, C1F5, C1F2
S10	7	C1F7, C3AcF, C1AcF, C3F6, C2AcF, C5F6, C1F4	C1F1, C2F1, C3F1, C4F1, C5F1, C1F2, C2F2	C3AcF, C1AcF, C2AcF, C1F6, C1F5, C1F4, C1F8	C1F3, C1AcF, C2AR1, C5AR15, C2AR15, C3AR14, C6AR15	C1F4, C1F5, C3AcF, C1F6, C1F3, C3F2, C4F6

selection method selected features one by one by confirming their highest contribution to the EMG-PR performance. Thus, the proposed feature selection method found the least number of features without compromising the EMG-PR performance. In this study, the proposed method with the KNN classifier achieved the highest EMG-PR performance with the lowest standard deviation compared to chi-square, reliefF, MRMR, and NCA (Section III).

The proposed method significantly improved the accuracy, sensitivity, specificity, precision, F1 score, and MCC by 3.18% to 4.28%, 9.14% to 12.85%, 1.83% to 2.57%, 8.30% to 10.99%, and 9.22% to 13.92%, 0.11 to 0.15, respectively when the proposed method was compared second-best performing feature selection method. In this study, the proposed feature selection method achieved forearm orientation and muscle force invariant F1 score of 91.46% for training KNN classifier with O1 and O3 with a medium force level. The achieved performance was much higher than the existing two works where they employed three orientations for training [19], [20]. Also, we trained the KNN classifier for all orientations with a medium force level and achieved the F1 score of 93.27%, which was improved by 2.27% to 2.92% [19], [20]. In addition to improved EMG-PR performances, the proposed feature selection method selected the least number of features of 7 to 20, less than the feature space used in the existing works (Table 5). So, the proposed feature selection method effectively reduces data dimensionality, design complexity, and hardware computational power, as defined in [19]. Again, the proposed method do not require any dimension reduction technique since the dimension of the selected feature is shallow. Therefore, the proposed feature selection method shows its robustness for resolving multiple limiting factors, forearm orientation, and muscle force variation, providing improved performance and selecting the least number of features.

In force invariant EMG-PR, the proposed feature selection method selected AcF, F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most of the subjects (Table 19), which implied that these features were the most stable features with muscle force variation. AcF and CC were selected since these features did not vary with muscle force levels, according to [14], [15]. The variation of muscle force level changed the values of F1, F2, F3, F4, F5, F6, F7, F8, and AR, but these features were selected due to the use of the signal normalization approach [14]. Again, in the case of forearm orientation and force invariant EMG-PR, the proposed feature selection method selected F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most of the subjects (Table 28) which implied that these features were stable with the forearm orientation and muscle force variation. It was also noted from Table 19 and Table 28 that AcF feature was common for force invariant EMG-PR, but it was not selected for the variation of both forearm and muscle force levels. So, accelerometer data changes with various forearm orientations. This research also used the proposed feature selection method when the KNN classifier was trained with a medium force level for all orientations. It was a kind of force invariant EMG-PR considering multiple orientations. So, the proposed method selected similar features in Table 19: AcF, F1, F2, F3, F4, F5, F6, F7, F8, CC, and AR in most of the subjects.

In this study, forearm orientation and muscle force invariant EMG-PR performance was highest when the KNN classifier was trained for O1 and O3 with a medium force level. The possible reason may be that the medium force level is highly correlated with each low and high force level, and O2 is in the middle position among the three orientations, so the angle of forearm rotation from O2 to each of O1 and O3 is minimum. So, it is suggested to use a force level for training so that other force levels are highly correlated. It is also recommended to use those orientations for training so that the angle of unknown testing orientation from the training orientation is minimum.

V. CONCLUSION AND FUTURE DIRECTIONS

This study has proposed an efficient feature selection method to resolve forearm orientation and muscle force variation in EMG-PR. The experimental results imply that the proposed feature selection method significantly improves the accuracy, sensitivity, specificity, precision, F1 score, and MCC by 3.18% to 4.28%, 9.14% to 12.85%, 1.83% to 2.57%, 8.30% to 10.99%, 9.22% to 13.92%, and 0.11 to 0.15, respectively when the proposed method is compared with second best-performing feature selection method. In this research, the proposed feature selection method achieves forearm orientation and muscle force invariant F1 score of 91.46% for training KNN classifier with O1 and O3 with a medium force level. Also, we achieve the F1 score of 93.27% training KNN classifier for all orientations with a medium force level. In addition to improved EMG-PR performances, the proposed feature selection method selects 7 to 20-dimensional features only. So, the proposed feature selection method does not require any dimension reduction technique and reduces the hardware's computational power. So, the proposed feature selection method would be an option to find efficient features and achieve improved EMG-PR performance with multiple limiting factors.

This research evaluates the performance using a machine, Intel Core i3-7100U CPU with 2.40 GHz processor and 8 GB RAM, whose computational power is relatively low. So, we considered the most efficient groups of feature extraction methods only. In our future study, other feature extraction methods, time-domain power spectral descriptors [24], wavelet bispectrum-based features [19], temporal-spatial descriptors [47], and traditional time-domain and frequency-domain features [39], will be investigated. In addition, this study resolves two factors, forearm orientation, and muscle force variation, but other limiting factors exist. So, our future study will include many limiting factors to make the EMG-PR system more robust, reliable, and user-friendly for prosthetic hand users. Again, our proposed feature selection algorithm is studied for an offline dataset including a limited number of subjects, comparatively simple hand gestures, and artifacts-free signal. So, the proposed feature selection will be studied for an online EMG-PR system considering these factors in our future study.

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APPENDIX A

See Tables 6–30.

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