Biomedical Signal Processing and Control 79 (2023) 104055

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Automated EEG sentence classification using novel dynamic-sized binary pattern and multilevel discrete wavelet transform techniques with TSEEG database

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A R T I C L E I N F O

Keywords:
EEG sentence classification
Dynamic sized binary pattern
Iterative multi-classifiers based majority voting
Neighborhood component analysis
Machine learning

A B S T R A C T

Electroencephalography (EEG) signal is an important physiological signal commonly used in machine learning to decode brain activities, including imagined words and sentences. We aimed to develop an automated lightweight EEG signal-based sentence classification model using a novel dynamic-sized binary pattern (DSBP) textural feature extractor and iterative multi-classifiers based majority voting (IMCMV) algorithm for iterative voting of results calculated using different classifiers for multi-channel EEG signal inputs. A new Turkish sentence EEG (TSEEG) was prospectively acquired. It comprised of 15-second 14-channel EEG signals recorded when 40 volunteers (for each dataset, we collected EEG signals from 20 participants) were either shown or read corresponding to demonstration or listening modes, respectively. Hence, 20 standardized commonly used sentences were obtained in their native Turkish language. The developed sentence classification model extracted 5,400 multilevel deep features from each channel EEG signal segment using the novel DSBP, statistical features, and multilevel discrete wavelet transform (MDWT). 512 features were then chosen using the neighborhood component analysis selection function. k-nearest neighbor and support vector machine classifiers were used to calculate two prediction vectors from the selected features using tenfold cross-validation, i.e., 28 vectors were generated for each 14-channel EEG recording. Finally, the best general voted results were determined for increasing numbers of iteratively calculated prediction vectors using the novel IMCMV algorithm. Channel-wise and voted results were found to be excellent for sentence classification for the TSEEG dataset in both demonstration and listening modes. The DSBP-IMCMV-based model attained the best general classification rates of 98.81% and 98.19% in the demonstration and listening modes, respectively.

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https://doi.org/10.1016/j.bspc.2022.104055
Received 26 April 2022; Received in revised form 19 July 2022; Accepted 8 August 2022
Available online 25 August 2022

1. Introduction

Communication is an important life skill and activity where individuals transmit information, feelings, and thoughts to other individuals using written or spoken words. Many real-world scenarios require non-verbal communication [1], especially in persons who have lost the ability to write or speak [2]. However, in afflicted individuals who still retain intact cognitive function [3], communication is still possible using non-verbal gestures, e.g., sign language. Alternatively, brain-computer interface devices have been developed that can be used to record and interpret brain activities to output the specific thought-generated activity signal as computer-generated text/speech fragments or robotics-aided physical movements [4]. These devices have been used in various medical applications to improve patients' quality of life with speech or motor impairment [5,6] and in non-medical applications [2,7].

To get brain activities, electroencephalography (EEG) signals are used extensively in clinics to assess the cognitive behavior of patients [8] and diagnose neuropsychiatric illnesses [9]. Indeed, EEG is the essential tool for studying brain activity signals in brain-computer interface applications. In a 23-subject silent/imagined speech recognition study using EEG signals, coarse- and fine-level classification accuracy rates of 85.20 % and 67.03 % were attained for the cognitive character, digit, or image classification tasks [3]. Kamble et al. [10] proposed an EEG classification model for imagined word recognition that combined decomposition processing, statistical feature extraction, Kruskal Wallis test-based feature selection, and classification, which they evaluated for binary and multiple class classification on three different datasets. DaSalla et al. [11] classified the imagined vowels "a" and "u" using a common spatial pattern for EEG signals feature extraction and support vector machine (SVM) classifier and reported a maximum accuracy of 78 %. In [12], a sigmoid function-based linear extreme learning machine was used to classify-five imaged words from the collected EEG signals of eight study participants. 40.3 % accuracy was attained for multi-class classification. Bakhshali et al. [13] employed correntropy spectral density matrices, Riemann distance, and k-nearest neighbor (kNN) classifier in their model to classify-four words and seven phonemes/syllables from EEG signals collected from eight subjects. In a similar study, the convolutional neural network (CNN) was combined with transfer learning to perform the classification of five vowels and six words from EEG signals collected from 15 subjects [14]. Salinas et al. [15] attained 68.18 % accuracy for classifying five words from EEG signals of 27 subjects using their proposed method. Panachakel et al. [16] proposed a deep learning architecture coupled with discrete wavelet transform (DWT) to decode imagined speech from 9-channel EEG signals and obtained 86.2 % accuracy. The same authors reported an average classification accuracy of 57.15 % using the same model on a different dataset [17]. In [18], two different convolutional neural networks, a common spatial pattern, and a linear discriminant analysis classifier were used to develop a new model for imagined speech recognition and attained maximum accuracy of 62.37 %. In addition, there are many studies on EEG signal classification in the biomedical field in the literature. Goshvarpour and Goshvarpour [19] proposed an epileptic seizure detection method using an EEG signal. They used two two-piece rose spiral curve model to detect epileptic seizures and attained an accuracy value of 100.0 % with SVM and kNN classifiers. Buriro et al. [20] used wavelet scattering transform and convolutional neural network to detect alcoholic EEG signals automatically. They have reported an accuracy of 100 % in detecting alcoholic EEG signals using SVM classifier using UCI dataset (EEG signals of 20 alcoholics subjects and 20 healthy subjects). Cherloo et al. [21] developed an EEG signal classification model for motor imagery. They applied ensemble regularized common spatio-spectral pattern. They reported an accuracy of 86.91 % and 82.64 % for BCI Competition III and BCI Competition IV, respectively. Wen et al. [22] presented a low power epilepsy detection approach using EEG signals. They obtained an accuracy of 91.86 % using lifting wavelet transform and SVM classifier. Wang et al. [23] applied statistical method to choose most discriminative feature using EEG signals. The main purpose of their study is to propose an effective feature extraction method and test the performance of the method. Their method obtained an accuracy of 81.99 % with SVM classifier. Baygin et al. [4] used collatz pattern and iterative neighborhood component analysis for schizophrenia detection with EEG signals. They attained accuracy value of 99.47 % and 93.58 % for datasets with 19 and 10 channels, respectively. Aydemir et al. [24] proposed a quadruple symmetric pattern for epilepsy disease detection. They obtained an accuracy of 98.40 % with kNN classifier using Bonn EEG dataset. Tuncer et al. [25] presented an epilepsy detection method using local senary pattern. They used 5 classes of Bonn EEG dataset and reported an accuracy of 93.00 % with SVM classifier.

As can be seen in the related works, researchers proposed models to classify vowel/words using EEG signals. However, their models are very complex to translate participants' situations. To handle this problem, we proposed a new methodology named EEG sentence classification.

We were inspired by EEG keyboard studies, where sentences can be translated directly from EEG signals [26,27]. In addition, most of the published studies in the literature have focused mainly on word, syllable, or letter classification [1,28,29] but not sentence recognition. We were thus motivated to develop an automated sentence classification model for multi-channel EEG signal inputs. Moreover, in most languages, a limited number of sentences are used to meet the daily routine. Also, we use certain sentences more often than other sentences. Therefore (using the frequency of individuals' use of sentence patterns), a new brain-computer interaction methodology is proposed, and this methodology is called EEG sentence classification. This is the first work about EEG sentence classification to the best of our knowledge. We chose small and primarily used Turkish sentences to create two EEG sentence datasets. Since the participants could not concentrate on thinking about long sentences, 20 short sentences, which are frequently used in Turkish, were used. Moreover, by using the selected 20 sentences, EEG observations with a small length can be used for classification.

In this work, we try to mimic the extraction of multileveled features using deep models by our computationally lightweight model coupled with multilevel discrete wavelet transform (MDWT) [30]. The statistical feature extractors and a novel dynamic-sized binary pattern (DSBP) textural feature extraction function is to generate multilevel low- and high-level features from input EEG signals. Hence, a novel iterative multi-classifiers-based majority voting (IMCMV) model was used to determine the best overall results from varying numbers of prediction vectors calculated from multiple classifiers and EEG signal channels. As a result, the proposed DSBP-IMCMV-based EEG sentence classification model, attained over 98 % classification accuracy on the study dataset.

The main contributions of this are given below:

- A novel feature extractor, DSBP was proposed that used non-fixed size overlapping blocks to generate textural features.
- A novel majority voting model, IMCMV, was proposed, which used the results of two classifiers on all channels in the EEG recording to generate overall performance metrics.
- A prospective EEG sentence dataset acquired in demonstration and listening modes was used to develop the proposed model.
- The generated automated DSBP-IMCMV EEG sentence classification model is computationally lightweight and attained over 98 % overall classification accuracy.

In this paper, the dataset is given in Section 2, the dynamic-sized binary pattern is mentioned in Section 3, and the proposed EEG sentence classification model is described in Section 4. Performance evaluation is presented in Section 5. Section 6 presents a discussion. Finally, the conclusion is given in Section 7.

Table 1
Twenty standardized Turkish sentences were used to elicit 1,600 15-second 14-channel EEG signal recordings from 20 volunteers in the demonstration and listening modes.

Number	Turkish sentence	English translation	EEG segments, (demonstration)	EEG segments (listening)
1	Merhaba, hoş geldiniz	Hello, welcome	80	80
2	Yine görüşürüz	See you again	80	80
3	Güle güle	Bye bye	80	80
4	Sağlik olsun	Never mind	80	80
5	Afiyet olsun	Enjoy your meal	80	80
6	Neye bakmiştiniz?	What are you looking for?	82	82
7	Bugün canli ders var mi?	Is there any online lecture today?	80	80
8	Hangi bölümde okuyorsun?	In which department are you a student?	79	79
9	Mesleğiniz nedir?	What is your job?	80	80
10	Bana güvenebilirsin	You can trust me	80	80
11	Sakin ol	Calm down	79*	79*
12	Defol git	Get out of here	80	80
13	Kolay gelsin	Good luck	80	80
14	Haydi gidelim	Let's go	80	80
15	Acele et	Hurry up	80	80
16	Hiç yoktan iyidir	It is better than nothing	80	80
17	Rica ederim	You're welcome	80	80
18	Sen bilirsin	It is your choice	80	80
19	Rezil ettiler bizi, rezil olduk	They disgraced us, we became disgraced	81	81
20	Hiçbir şey bilmiyorsun	You know nothing	79	79

2. Dataset

A Turkish sentence-EEG sentence (TSEEG) dataset was recorded when subjects were either shown or read—demonstration or listening modes, respectively. Finally, 20 standardized commonly used sentences in their native Turkish language (Table 1) were obtained. In the demonstration mode, the sentences were shown via computer terminal screens to 20 volunteers (16 males, age range 19 to 23 years, mean age 21.35 $\pm$ 1.20 years; 4 females, age range 19 to 23 years, mean age 20.50 $\pm$ 1.73 years); in the listening mode, the sentences were read via computer audio output to another 20 volunteers (17 males, age range 19 to 24 years, mean age 21.74 $\pm$ 1.39 years; 3 females, age range 20 to 23 years, mean age 21 $\pm$ 1.73 years). Throughout, EEG signals were acquired from all the volunteers using the EMOTIV EPOC + mobile system, which collected 14-channel EEG signals from 16 scalp zones: AF3 (1), F7 (2), F3 (3), FC5 (4), T7 (5), P7 (6), O1 (7), O2 (8), P8 (9), T8 (10), FC6 (11), F4 (12), F8 (13), AF4 (14), *P*3 (reference zone), and *P*4 (reference zone) (Fig. 1). Each EEG signal segment lasted 15 s (sampling rate 128 Hz, bandwidth 0.16–43 Hz) and was pre-processed on the EMOTIV EPOC + system before input into our EEG classification model. For classification in this study, each EEG recording contained 14 EEG signals channels. Therefore, each Turkish sentence was considered one class, i.e., results would be reported in either channel-wise or 20-class classification performance.

The system comprised saline wet EEG electrodes in set positions that could be conveniently applied to the unshaven scalps of volunteers for the experiments. The Turkish sentences were shown to volunteers on the computer screens in demonstration mode. The Turkish sentences were read to volunteers in listening mode over the computer audio output. For every Turkish sentence, one 15-second 14-channel EEG recording was acquired. The demonstration and listening modes of the experiments were conducted in separate groups of male and female volunteers.

3. Dynamic sized binary pattern

In this work, we have proposed a new textural feature extractor to improve feature extraction ability of the classical textural feature extractor. The DSBP is an improved version of a one-dimensional local binary pattern [31] which employed four overlapping blocks with identical centers and dynamically sized window lengths of 3, 5, 7, and 9 to extract binary features using center symmetric and center-based feature extractions strategies (Fig. 2).

The rectangles represent signal data elements of the blocks, with the center values shown in red. Overlapping windows with lengths of 3,5, 7, and 9 define the center value. A total of 30 bits were generated based on relationships (depicted as blue lines connecting the rectangles) of elements equidistant from the center in center symmetric feature extraction (10 bits generated) and relative to the center in center-based feature extraction (20 bits generated).

Detailed steps of DSBP feature extraction are given below.

1. Divide the one-dimensional signal into overlapping blocks with nine lengths.

$$blc^1 = signal(k+l-1), k \in \{1,2,\cdots,len\}, l \in \{1,2,\cdots,9\} \quad (1)$$

where blc^1 represents the overlapping block with a length of nine.

2. Create sub-blocks using the *blc*.

$$blc^h = blc^{h-1}(1+t), t \in \left\{1,2,\cdots,leng\left(blc^{h-1}\right)-2\right\}, h \in \{2,3,4\} \quad (2)$$

Fig. 1. EEG signal collection from female (left) and male (right) volunteers using the commercial EMOTIV EPOC + mobile system wirelessly connected to the computer terminal.

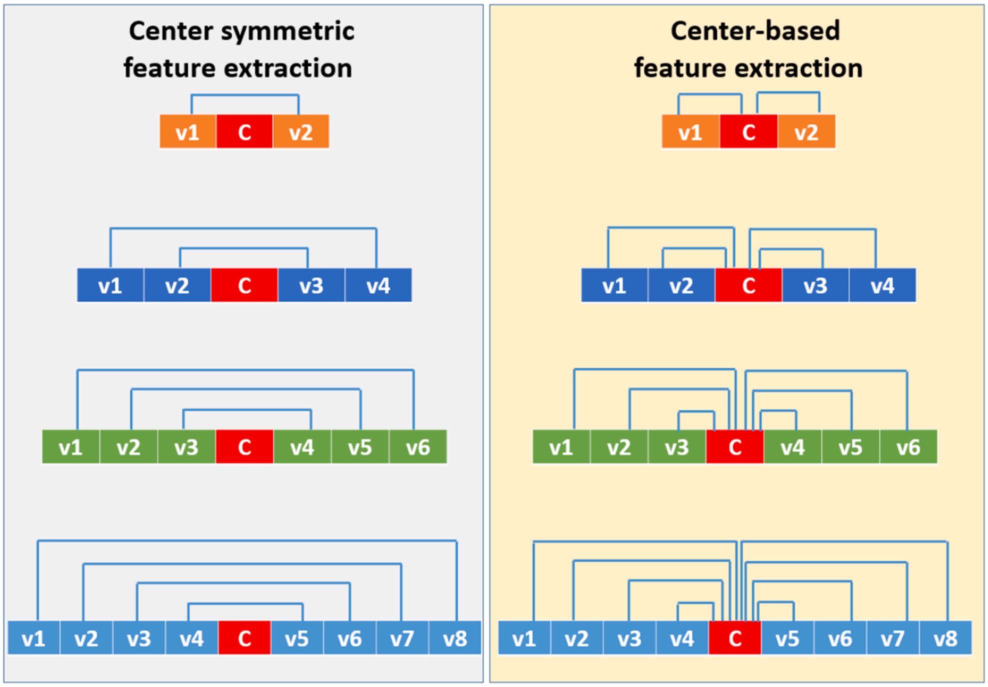

Fig. 2. DSBP-based center symmetric and center-based feature extraction.

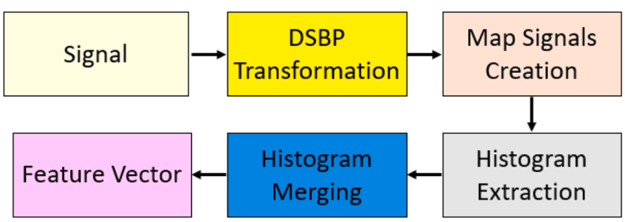

Fig. 3. The graphical denotation of the presented DSBP feature extractor.

where *leng*(.) is the length calculation function.

3. Extract binary features using the generated non-fixed size overlapping blocks and signum function. The schematic depiction of the DSBP feature extraction function is depicted in Fig. 3.

The bit extraction operation is shown in Algorithm 1.

Algorithm 1. Pseudocode of DSBP-based binary feature extraction.

Input: Blocks (*blc*) with lengths of 3,5,7,9.
Output: Binary features (*bit*) with a length of 30.
$cnt = 1$;
// Center symmetric bit extraction
for k=1 to 4 **do**
  for i=1 to $\left\lfloor \frac{length(blc^k)}{2} \right\rfloor$ **do**
    $bit(cnt) = \rho(blc^k(i), blc^k(length(blc^k) + 1 - i))$;
    $cnt = cnt + 1$;
  end for i
end for k
// Center-based bit extraction
for k = 1 to 4 **do**
  $center = \left\lceil \frac{length(blc^k)}{2} \right\rceil$; // Assign center value.
  for i = 1 to $length(blc^k)$ **do**
    if $i! = center$ **then**
      $bit(cnt) = \rho(blc^k(i), blc^k(center))$;
      $cnt = cnt + 1$;
    end if

(*continued on next column*)

(*continued*)

Algorithm 1. Pseudocode of DSBP-based binary feature extraction.

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  end for i
end for k

In Algorithm 1, *cnt* represents counter; *length*(.), length calculation function; $\rho(.)$, signum function, which is mathematically defined as:

$$\rho(a,b) = \begin{cases} 0, a - b < 0 \\ 1, a - b \geq 0 \end{cases} \quad (3)$$

where a, b represent the input parameters.

4. Divide the 30 generated bits into five non-overlapping bit groups, each with six bits.

$$bg^t(i) = bit(i + 6 \times (t-1)), i \in \{1, 2, \cdots, 6\}, t \in \{1, 2, \cdots, 5\} \quad (4)$$

where bg^t is t[th] bit group.

5. Calculate five map signals using the five generated 6-bit groups.

$$m^t(i) = \sum_{j=1}^{6} bg^t(j) \times 2^{6-j} \quad (5)$$

where binary to decimal conversion/transformation was performed, and m^t defines t[th] map signal.

6. Generate histograms of the calculated map signals. The length of each histogram was 64 (=2^6).
7. Merge the generated histograms to obtain the feature vector of the DSBP.

$$x(j) = h^t(j + 64 \times (t-1)), j \in \{1, 2, \cdots, 64\}, t \in \{1, 2, \cdots, 5\} \quad (6)$$

where x represents the generated feature vector with a length of 320; and h^t, histogram of the t[th] map signal.

Equations (1) to (6) define the proposed DSBP feature generation function ($\delta(.)$).

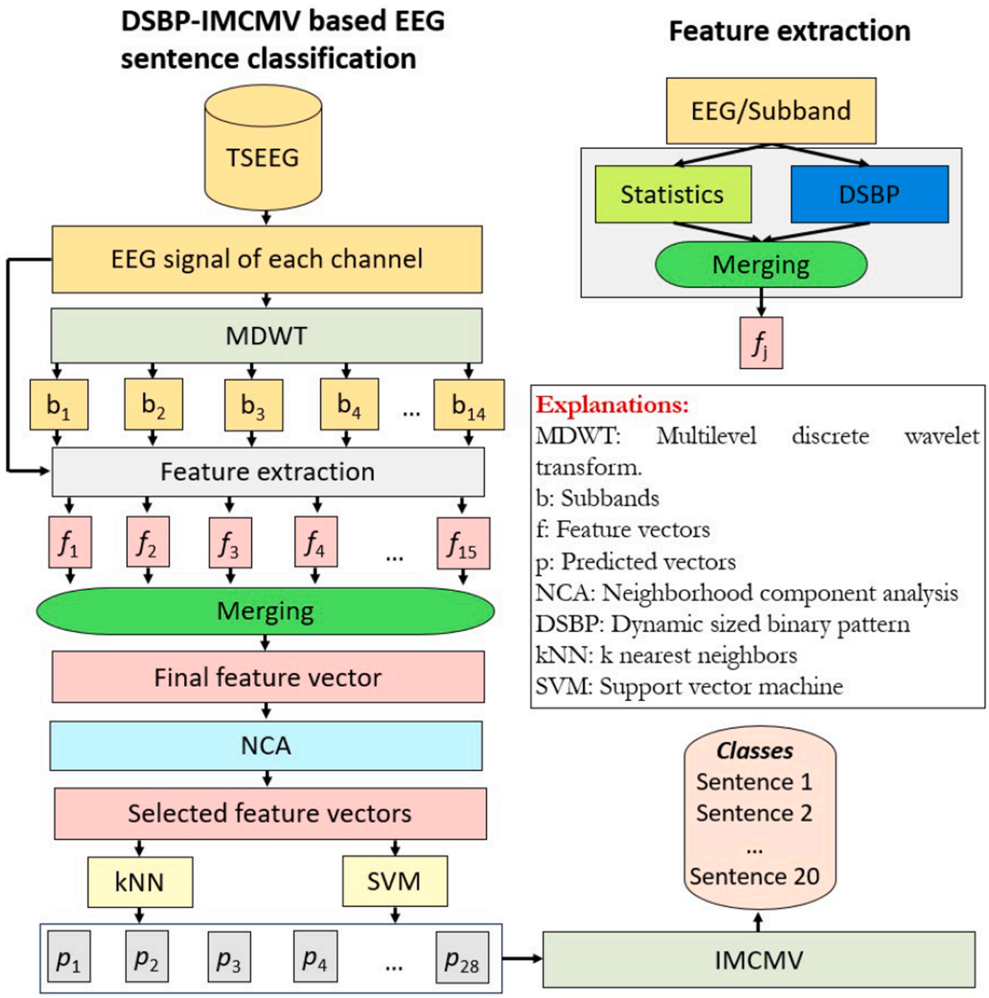

Fig. 4. Block diagram of the proposed DSBP-IMCMV model with input TSEEG dataset.

4. Proposed EEG sentence classification model

The one-dimensional signal classification model comprised *four* phases: (i) hybrid feature extraction using DSBP, statistics [32], and MDWT [33]; (ii) selection of top features using neighborhood component analysis (NCA) [34]; (iii) signal classification of each channel using kNN [35] and SVM [36]; and voting of general results from all channels using IMCMV algorithm (Fig. 4).

A 7-level MDWT was used to calculate high-pass and low-pass filter subbands of EEG signal segments from all 14 channels that constitute each 15-second EEG recording acquired in response to shown or read Turkish sentences. DSBP and statistical generator functions were used to extract 320 and 40 features, respectively, from each of the 14 MDWT-derived subbands and the original input EEG signal of the channel. The 15 feature vectors (f) each of length 360 generated for each EEG signal segment were merged to form a large feature vector of length 5,400 (=15 × 260), from which the top 512 features were chosen using the NCA selector. SVM, and kNN with tenfold cross-validation were used to calculate two validation prediction vectors for each channel, i.e., 28 predicted vectors were calculated for each 14-channel EEG recording. Finally, IMCMV algorithm was used to determine the best general classification result for all EEG signal inputs per channel.

Our proposed feature engineering model consists of four main phases. These phases are (i) hybrid and multilevel feature extraction with MDWT and two feature selection function (DSBP and statistics), (ii) NCA-based the most informative features selection, (iii) classification with two shallow classifiers (kNN and SVM), (iv) majority voting for the best results selection. Furthermore, detailed steps of the DSBP-IMCMV-based model are given below phase-by-phase.

4.1. Feature extraction

We have proposed a hand-crafted feature engineering model. Thus, the most important phase of this model is feature extraction. In this phase, we have used MDWT to generate a multileveled feature extraction method. Moreover, the handcrafted feature extraction contains two main methodologies: (i) statistical and (ii) textural. Therefore, we have used 20 well-known linear and nonlinear statistical moments to generate statistical features, and a new feature generation function (DSBP) has been proposed to extract textural features.

Step 1: Read each EEG signal segment input (sampling rate 128 Hz, duration 15 s) from individual channels. The length of each signal segment was 1,920 (=128 × 15).

Step 2: Decomposed EEG signal into subbands (b) using MDWT transform (Fig. 3). Here, MDWT with seven levels was used. The number of levels was calculated using the following formula:

$$lev = \left\lfloor \log_2\left(\frac{len}{lb}\right) \right\rfloor \tag{7}$$

where *lev* represents the number of levels; *len*, the length of EEG signal; and *lb*, the maximum length of the deployed overlapping blocks. , The schematic expression of the MDWT, is demonstrated in Fig. 5.

In the literature, generally, multilevel wavelet transformation has

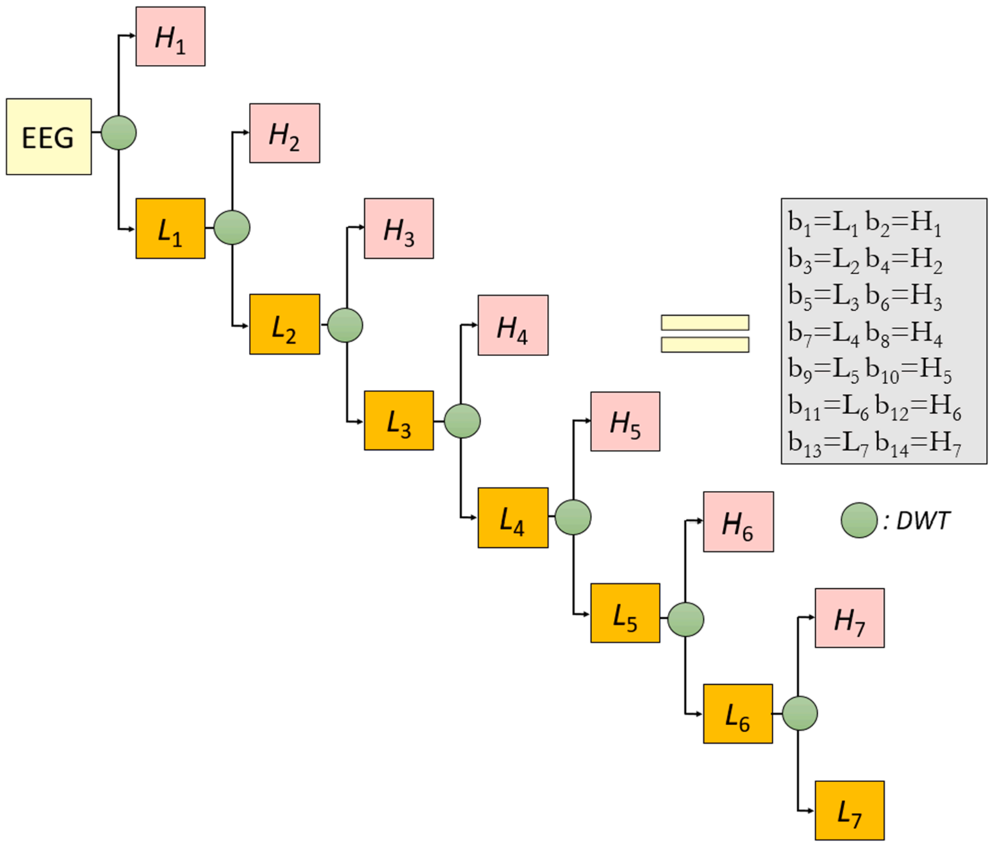

Fig. 5. Illustration of MDWT with seven levels. Symlet 4 mother wavelet function was used to generate subbands *b*, each containing low-pass (L) and high-pass (H) filter coefficients.

been used to generate wavelet coefficients to generate features in the frequency domain, but most researchers have used low-pass filter subbands to generate features. We have used a hybrid approximation since we want to benefit from the feature generation ability of the high-pass filter subbands. Thus, we have used high-pass filter subbands to generate features like wavelet packet decomposition [37,38]. Furthermore, we have used the symlet4 filter. This filter has generally used for signal denoising. Thus, we have used this function. The subband generation using the MDWT model is mathematically explained below.

$$[L_1, H_1] = \Psi(EEG, sym4) \tag{8}$$

$$[L_g, H_g] = \Psi(L_{g-1}, sym4), g \in \{2, 3, \cdots, 7\} \tag{9}$$

where L and H represent low-pass and high-pass filter coefficients, respectively; and $\Psi(.,.)$, the discrete wavelet transform function, and it takes two parameters: input signal and wavelet filter. Here, symlet 4 (*sym*4) filter was used. Using the generated subbands (L and H), the model's band data structure was created (Fig. 2).

$$b_{2k-1} = L_k, k \in \{1, 2, \cdots, 7\} \tag{10}$$

$$b_{2k} = H_k \tag{11}$$

Step 3: Generate feature vectors from b and the original EEG signal using statistical and DSBP feature extractors.

$$f_1 = \gamma(\varpi(EEG), \delta(EEG)) \tag{12}$$

$$f_{j+1} = \gamma(\varpi(b_j), \delta(b_j)), j \in \{2, 3, \cdots, 14\} \tag{13}$$

where f are feature vectors; $\gamma(.)$, concatenation/merging function; $\varpi(.)$, statistical feature extractor; and $\delta(.)$ is DSBP feature extractor. Details of $\varpi(.)$ and $\delta(.)$, which extracted 40 and 320 features, respectively, from each subband or input EEG signal, are given below. The used statistical feature extraction has been explained below.

Statistical feature extraction is a fast and effective method [39]. In this paper, twenty commonly used statistical moments were applied to each one-dimensional signal and its absolute value to extract 40 features from each one-dimensional signal. The statistical feature extraction used in this study includes both linear (median, maximum, minimum, mode, variance, skewness, standard deviation, kurtosis, average, range, Higuchi, largest Lyapunov exponent) and nonlinear (energy, Renyi, Shannon, Kolmogorov-Sinai, Fuzzy, Tsallis, Wavelet and Permutation entropy) methods [40].

We used textural and statistical features to generate a fused feature vector.

Step 4: Concatenate the generated feature vectors.

$$X(j) = f^l(q + 64 \times (l - 1)), q \in \{1, 2, \cdots, 360\}, l \in \{1, 2, \cdots, 15\} \tag{14}$$

where X represents the calculated final/united feature vector with a length of 5,400 (=360 × 15).

Steps 1 to 4 above define the proposed multilevel hybrid feature extraction process.

4.2. Feature selection

In this work, we have used a simple feature selection function, which is a distance-based function. This function is NCA and NCA is a selection version of the kNN. NCA generates nonnegative weights for features, which have been used to choose the most informative features (high weights assign the distinctive features and low weights define the redundant features). Thus, the generated weights have been sorted by descending to obtain the qualified indexes of the features. The most informative/valuable features can be selected using the computed

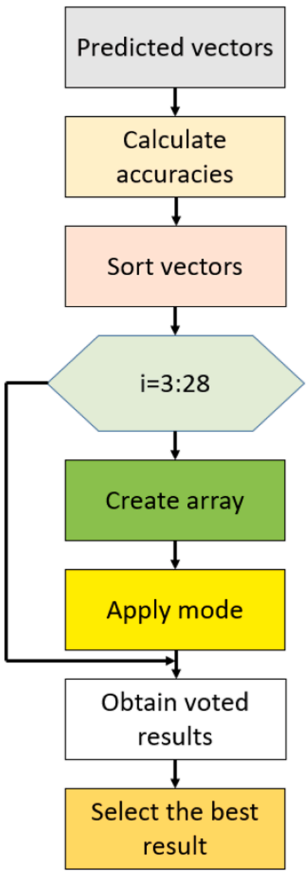

Fig. 6. The used IMCMV algorithm to get the best classification result.

indexes. Furthermore, NCA is both a simple and effective feature selection function. Thus, we selected NCA as a feature selector. In this research, the most valuable 512 features have been selected.

Step 5: Choose the most valuable/important 512 features using the NCA feature selector.

NCA, the feature selection counterpart of the kNN, is a simple selector that is widely used in the literature.

4.3. Classification

To demonstrate the high classification ability of the generated features using the proposed feature extraction method and NCA, we have used two shallow classifiers: kNN and SVM. MATLAB classification learner tool was used to choose the most suitable classifiers. Per the calculated test results, the best two classifiers are kNN and SVM. Thus, we used these classifiers as validation prediction vector generators.

Step 6: Calculate validation prediction vectors using kNN and SVM with 10-fold cross-validation. Two predicted vectors were created for each channel's EEG signal segment, which was the first step of the proposed IMCMV.

$$p^{2c-1} = \mathrm{K}(sf_c, y, 10), c \in \{1, 2, \cdots, 14\} \tag{15}$$

$$p^{2c} = \Phi(sf_c, y, 10) \tag{16}$$

where p represents the predicted vectors; sf, features selected by NCA; y, actual output; the value "10", 10-fold cross-validation; $\mathrm{K}(.)$, kNN classifier; and $\Phi(.)$, SVM classifier. Hyperparameters of the classifiers are given below:

k-nearest neighbor (kNN) [35]:

k was 1, city block (L1-norm) distance metric was used, and there was no voting.

Support vector machine (SVM) [36]:

A second-degree polynomial kernel was used, the box constraint level was one, and coding was chosen as 1-vs-1.

4.4. Majority voting

In this work, we have proposed a new majority voting algorithm. This majority voting model uses a loop to generate more than one voted vector, and we have used predicted vectors of two classifiers. Thus this model is named iterative multi-classifiers-based majority voting (IMCMV). The graphical summarization of this phase is given in Fig. 6.

Steps of this phase are given below.

Step 7: Compute the accuracy of each channel using p and y.
Step 8: Apply iterative (loop-based) mode-based majority voting to calculate general results.

Algorithm 2. Pseudocode of IMCMV.

```
Input: Predictions (p), accuracies (oa).
Output: Voted predictions (vp).
Calculate indexes sorted (idx) using the calculated acc.
for g = 3 to 28 do // Iterative voting
  for i = 1 to length(y) do
    for j = 1 to g do
      arr(j) = p_idx(j)(i);
    end for j
    vp_g-2(i) = M(arr); // M(.) is mode function.
  end for i
end for h
```

Step 9: Calculate accuracies voted using vp and y.
Step 10: Choose the best result.

5. Performance evaluation

The proposed DSBP-IMCMV-based EEG classification model was programmed using MATLAB2021a on a personal computer with 32 GB memory, Intel i9-9900 processor, and Windows 10.1 ultimate operating system without executing parallel processes or needing graphical or tensor processing units.

5.1. Classification measurements

Standard performance metrics—accuracy (Oa), precision (Pr), recall (Rc), and F1-score ($F1$) [41,42]—were used to calculate channel-wise and voted results to evaluate the proposed model. Mathematical formulae of the metrics are listed below.

$$Rc = \frac{TP}{TP + FN} \tag{17}$$

$$Pr = \frac{TP}{TP + FP} \tag{18}$$

$$Oa = \frac{TP + TN}{TP + FP + TN + FN} \tag{19}$$

$$F1 = 2\frac{Rc \times Pr}{Rc + PR} \tag{20}$$

where TP, FP, TN, and FN are true positives, false positives, true negatives, and false negatives, respectively.

Table 2
Channel-wise results (%) obtained using our proposed model on TSEEG signals acquired in demonstration mode stratified by kNN and SVM classifiers.

Ch. No	kNN				SVM			
	Oa(%)	*Rc*(%)	*Pr*(%)	*F*1(%)	*Oa*(%)	*Rc*(%)	*Pr*(%)	*F*1(%)
1	88.38	88.38	88.48	88.43	91.31	91.32	91.65	91.48
2	91.06	91.06	91.15	91.11	90.75	90.75	90.89	90.82
3	89	89.01	88.99	89	90.50	90.51	90.70	90.60
4	87.75	87.74	87.84	87.79	90	90	90.48	90.24
5	89.50	89.46	89.56	89.51	90.88	90.85	91.01	90.93
6	90.25	90.24	90.29	90.26	88.88	88.87	89.27	89.07
7	89.75	89.72	90.04	89.88	90.38	90.36	90.81	90.59
8	**94.69**	**94.69**	**94.83**	**94.76**	**93.69**	**93.69**	**93.98**	**93.83**
9	92.13	92.11	92.30	92.20	92.06	92.06	92.52	92.29
10	92.38	92.37	92.49	92.43	92.63	92.62	92.85	92.73
11	92.31	92.32	92.43	92.37	91.81	91.82	92.17	91.99
12	86.44	86.43	86.64	86.53	88.69	88.68	89.23	88.95
13	83.56	83.58	83.65	83.62	87.56	87.56	87.88	87.72
14	90.31	90.32	90.36	90.34	91	91	91.22	91.11

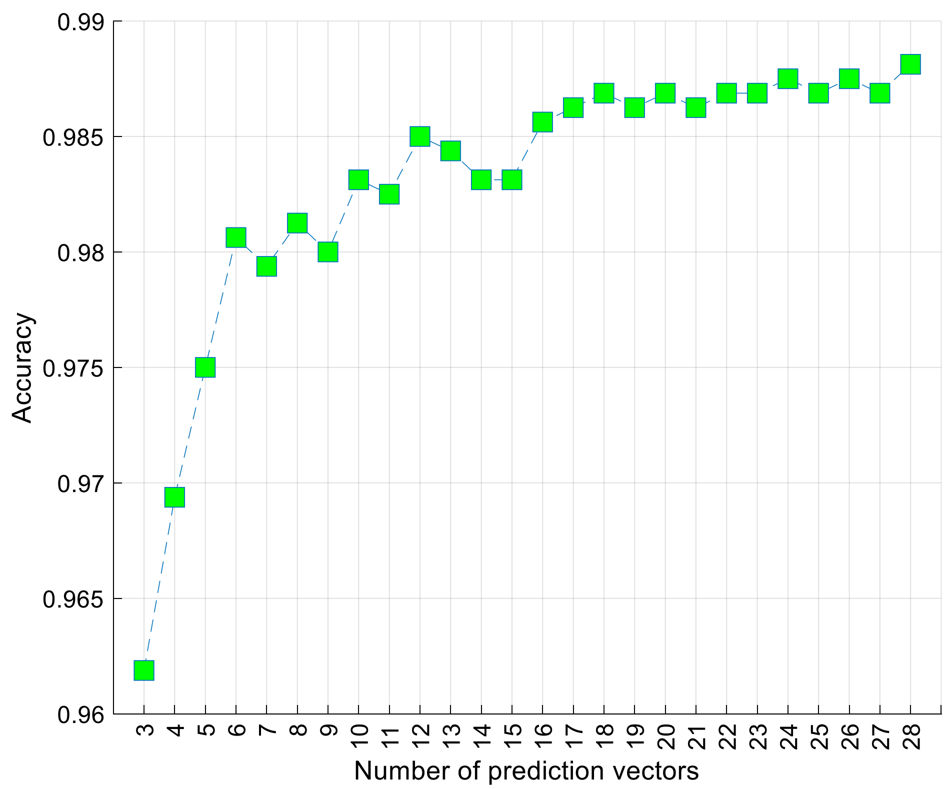

Fig. 7. Plot of voted accuracies versus the number of prediction vectors used on TSEEG signals acquired in demonstration mode.

5.2. *Demonstration mode results*

The model attained good to excellent channel-wise results using kNN and SVM classifiers, with the best performance seen in Channel 8. (Table 2). The overall classification accuracy rates across all channels were 89.82 %±2.79 % and 90.72 %±1.62 % using kNN and SVM classifiers, respectively.

Using IMCMV algorithm, 26 more voted results with corresponding accuracies were iteratively calculated. By deploying IMCMV, the model achieved (worst) an accuracy of 96.19 % using the minimum of three predicted vectors and the best accuracy of 98.81 % using all 28 predicted vectors (Fig. 7).

The confusion matrix of the model obtained using TSEEG signals acquired in demonstration mode shows low misclassification rates (Fig. 8). In the worst case, Turkish sentence Number 9 "Mesleğiniz nedir?" ("What is your job?") in the demonstration mode was misclassified eight times as Turkish Sentence Number 17 "Rica ederim" ("You're welcome") (Table 1).

5.3. *Listening mode results*

The model attained good to excellent channel-wise results, with the best performance obtained for Channels 7 and 10 for the kNN and SVM classifiers, respectively (Table 3). The overall classification accuracy rates across all channels were 92.48 %±2.61 % and 92.27 %±1.94 % using kNN and SVM classifiers, respectively.

By deploying IMCMV, the model achieved an accuracy result of 96.56 % using the minimum of three predicted vectors and the best accuracy result of 98.19 % using 15 predicted vectors (Fig. 9).

The confusion matrix of the model for TSEEG signals acquired in listening mode shows low misclassification rates (Fig. 10). In the worst case, Turkish sentence Number 3 "Güle güle" ("Bye bye"), in the

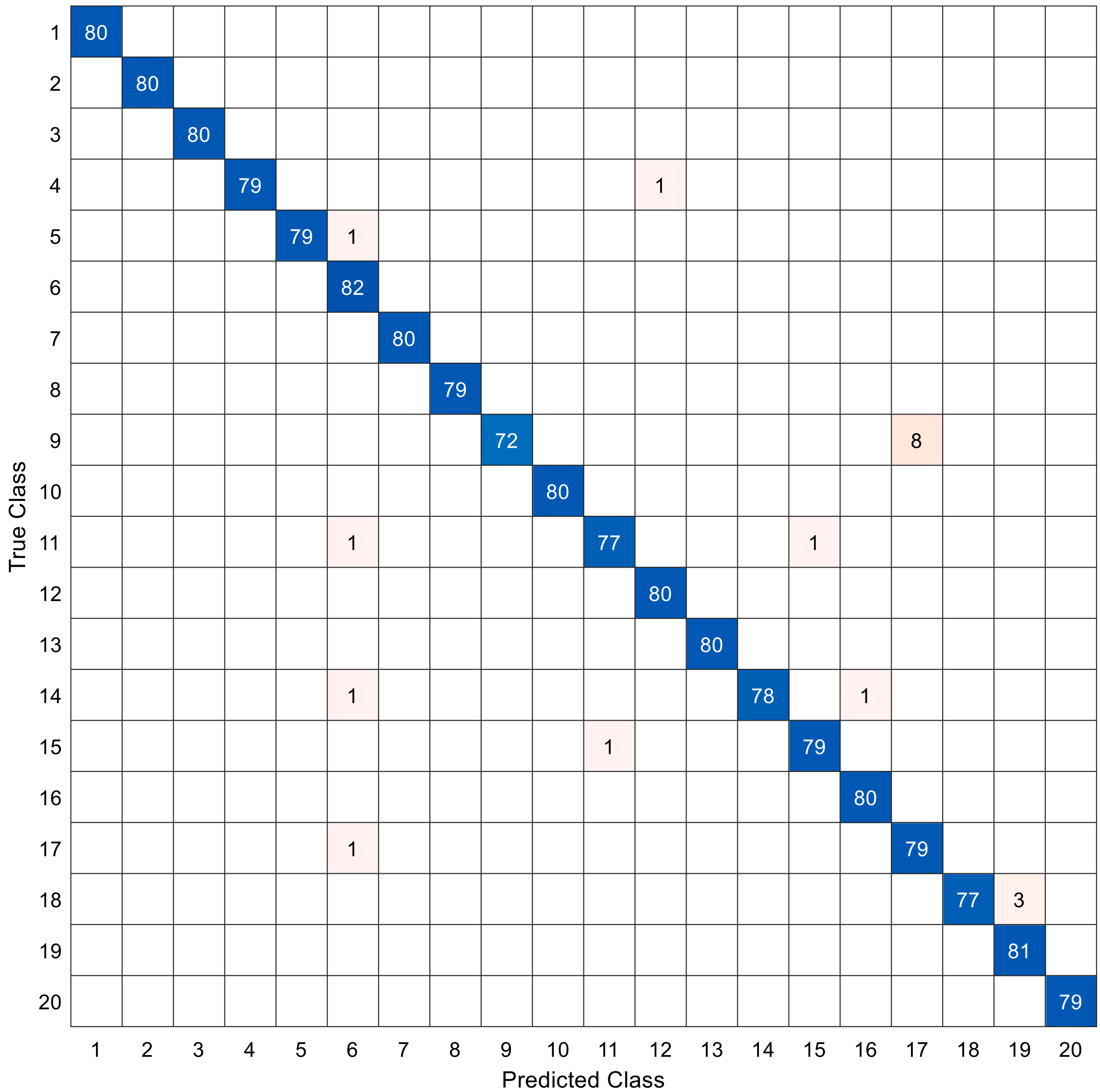

Fig. 8. Confusion matrix of the voted results for TSEEG signals acquired in demonstration mode. Each enumerated true class corresponds to the enumerated Turkish sentence listed in Table 1.

Table 3
Channel-wise results (%) obtained using our proposed model on TSEEG signals acquired in listening mode stratified by kNN and SVM classifiers.

Ch. No	kNN				SVM			
	Oa(%)	*Rc*(%)	*Pr*(%)	*F*1(%)	*Oa*(%)	*Rc*(%)	*Pr*(%)	*F*1(%)
1	91.94	91.92	91.98	91.95	92.56	92.54	92.75	92.65
2	93.38	93.36	93.45	93.41	92.38	92.36	92.47	92.42
3	90.13	90.12	90.23	90.18	90.13	90.11	90.60	90.35
4	93.75	93.75	93.80	93.77	92.50	92.49	92.67	92.58
5	92.94	92.93	93.13	93.03	93.69	93.69	93.95	93.82
6	93.50	93.49	93.71	93.60	92.94	92.94	93.12	93.03
7	**95.25**	**95.24**	**95.39**	**95.32**	94.31	94.31	94.48	94.40
8	95.06	95.06	95.09	95.08	93.75	93.73	93.96	93.85
9	95.06	95.06	95.13	95.09	93.81	93.80	93.98	93.89
10	94.25	94.24	94.34	94.29	**94.63**	**94.62**	**94.74**	**94.68**
11	92.63	92.62	92.76	92.69	92.44	92.43	92.51	92.47
12	89.19	89.17	89.40	89.29	89.75	89.73	90.09	89.91
13	85.88	85.86	85.88	85.87	87.81	87.80	88.33	88.07
14	91.81	91.80	91.80	91.80	91.13	91.11	91.27	91.19

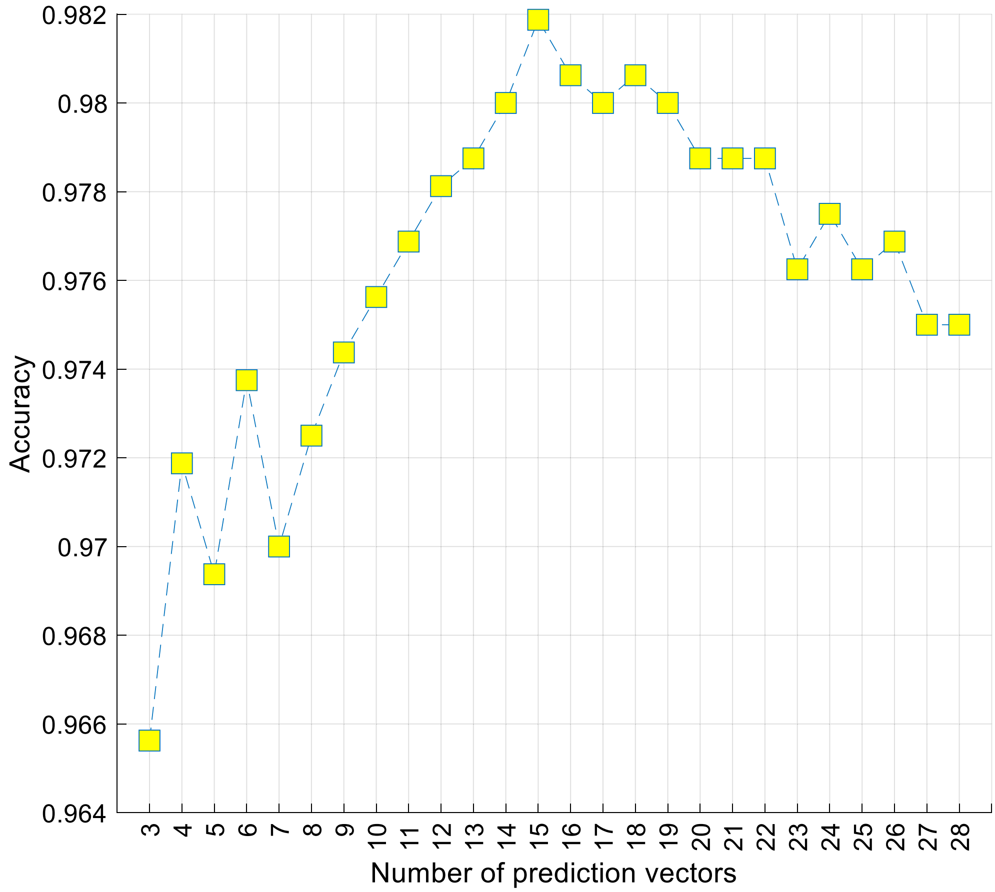

Fig. 9. Plot of voted accuracies versus the number of prediction vectors used in listening mode.

listening mode, was misclassified twelve times as Turkish Sentence Number 13 "Kolay gelsin" ("Good luck") (Table 1).

6. Discussion

In this work, an EEG sentence classification model was developed using a prospective EEG dataset, TSEEG, which was acquired from two different sets of twenty volunteers who were either shown or read—demonstration and listening modes, respectively—twenty standardized Turkish sentences in their native language. The study of the two distinct modes and the use of separate groups of volunteers for the demonstration and listening modes were essential considerations in the experimental setup. The visual and auditory neural pathways in the brain are distinct. Their processing of sentence recognition and the induced EEG signals will be different. Hence, the need for separate experiments and separate groups of volunteers for the experiments to preempt potential signal contamination from repeat exposure.

A new lightweight classification model, which employed novel DSBP and IMCMV methods, was trained and tested on the TSEEG dataset to develop an accurate EEG sentence classification system. DSBP and statistical feature extractors were deployed to extract local textural features and low-level statistical features. However, the MDWT decomposes the EEG signals into low- and high-pass subbands. Hence, it feeds the DSBP and statistical feature extractors, both low- and high-level features generated at multiple levels. 5,400 features were generated per input EEG segment, and NCA selector was used to choose the top 512 features. In the classification phase, kNN and SVM classifiers were employed to generate two prediction vectors per EEG signal channel. In the demonstration mode, the best channel-wise results were obtained from Channel 8 (O2), which collected surface EEG signals near one of the occipital lobes in the brain. This observation supports the occipital lobes' essential role in processing visual information, as exemplified by sentences shown to respondents on a computer terminal screen in the demonstration mode of the study experiments.

In contrast, the channel-wise results in the listening mode are different, with the best performance observed in Channels 7 (O1) and 10 (T8), with kNN and SVM classifiers, respectively. The temporal lobe has a critical role in auditory management, and the occipital lobe manages the brain's visual system. In our experiment, we collected EEG signals using listening and demonstrating. Moreover, we said to participants, "please only think about this sentence". Therefore, these lobes were activated in the data collection phase, and we obtained the best results from these channels 7,8, and 10.

As each EEG recording contained 14 channels, 28 prediction vectors were generated for each of the 1,600 EEG recording samples from the TSEEG dataset. IMCMV was used to calculate voted results and select the best overall results among all the channels of individual EEG recordings. Based on results voted using increasing numbers of iteratively generated prediction vectors, the optimal number of prediction vectors was not always the maximum number of 28 (Figs. 5 and 7). Using IMCMV, the best overall accuracy, recall, precision, and F1 score were found to be 98.81 %, 98.81 %, 98.88 %, and 98.84 %, respectively, with 28 prediction vectors in the demonstration mode; and 98.19 %, 98.19 %, 98.28 %, and 98.23 %, respectively, with 15 prediction vectors in the listening mode. Twenty commonly used Turkish sentences had been arbitrarily chosen in the experiments, and it could not be ascertained *a priori* that all sentences were suitable for training and testing the model. Accordingly, it was essential to evaluate the model's class-wise classification results to ascertain minimum satisfactory performance for all classes (i.e., Turkish sentences) used in the experiments. Class-wise accuracy rates of all 1,600 recording samples in the dataset were excellent (Fig. 11). Twelve and nine classes attained 100 % class-wise accuracy

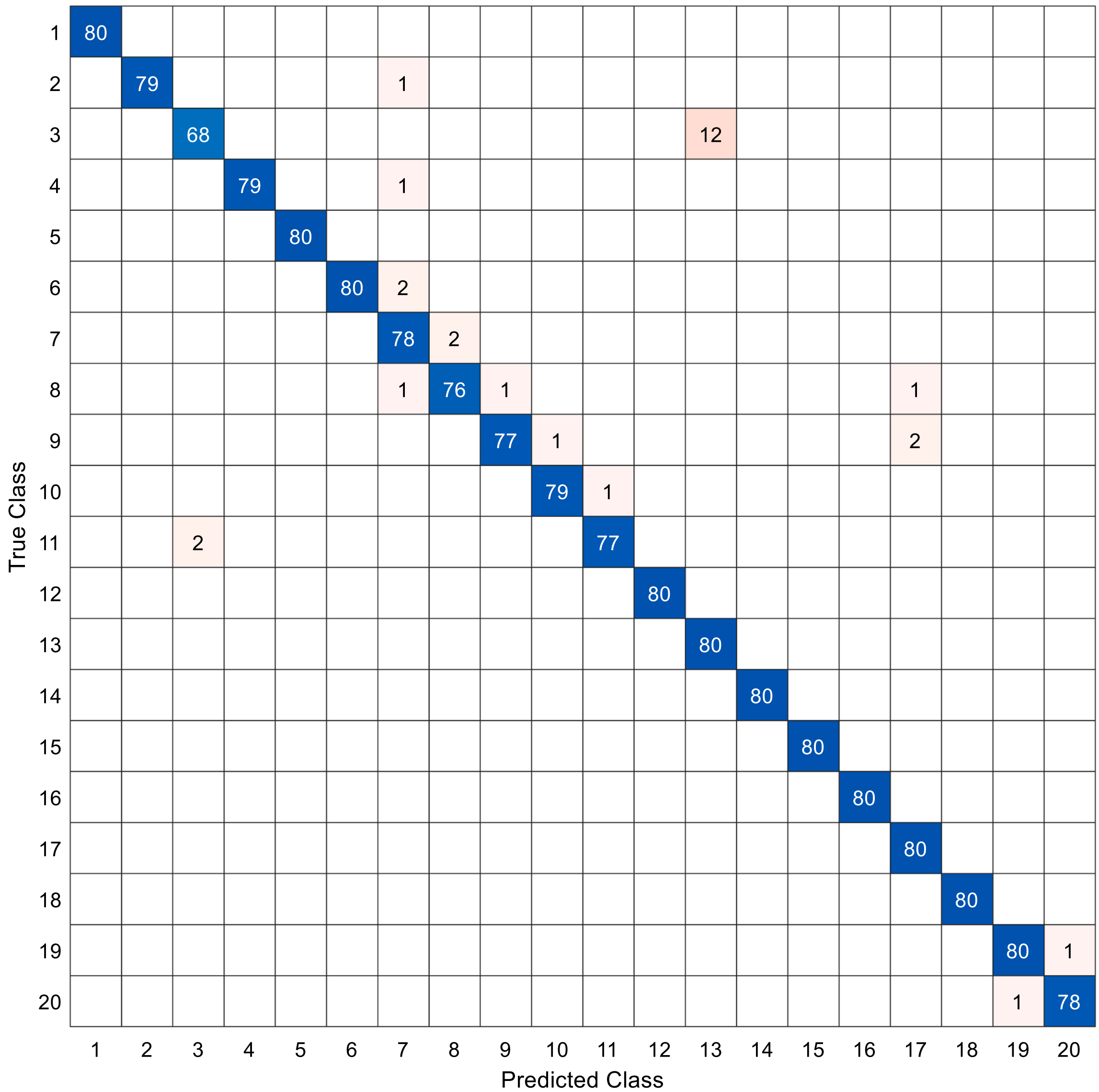

Fig. 10. Confusion matrix of the voted results for TSEEG signals acquired in listening mode. Each enumerated true class corresponds to the enumerated Turkish sentence listed in Table 1.

rates in the demonstration and listening modes, respectively. The worst accuracy rates were observed in Classes 9 (90 %) and 3 (85 %) in the demonstration and listening modes, respectively. In addition, the findings of the confusion matrices (Figs. 8 and 10) illustrate this situation. However, these results can be considered satisfactory for study experiments.

To get comparative results, we selected the best accurate channels for demonstration and listening datasets. For the demonstration-based EEG dataset, the best accurate channel is the 8th channel and the 7th channel is the best for the listening-based EEG dataset. Thus, we applied tests on these channels. The used models for comparisons are (i) statistics, (ii) local binary pattern, (iii) ternary pattern, (iv) Hamsi pattern [43] and (v) Twine-shuffle pattern [30]. The calculated classification accuracies have been tabulated in Table 4.

As seen from Table 4, our proposal attained the best classification accuracy among these models and demonstrated the superiority of the proposed DSBP-IMCMV-based EEG classification model. Furthermore, Table 4 highlighted that the multilevel and hybrid feature extraction increased classification performance.

The advantages and limitations of the proposed model are listed below.

Advantages:

- In separate groups of volunteers, a new EEG sentence dataset was prospectively acquired in two modes—demonstration and listening—to develop the model.
- DSBP, an improved version of the one-dimensional local binary pattern [31], was deployed to extract textural features, including high-level features from subbands of EEG signals decomposed by MDWT.
- A new voting model, IMCMV, was proposed to select the best overall results from multiple classifiers and multiple EEG signal channels from iteratively voted results using increasing numbers of calculated prediction vectors.
- The proposed DSBP-IMCMV-based model is simple and robust.
- The model attained over 98 % classification accuracy rates for one-dimensional EEG signals using the TSEEG dataset for both demonstration and listening modes. Therefore, we expect the model to also be used to classify other one-dimensional signals.

Limitations:

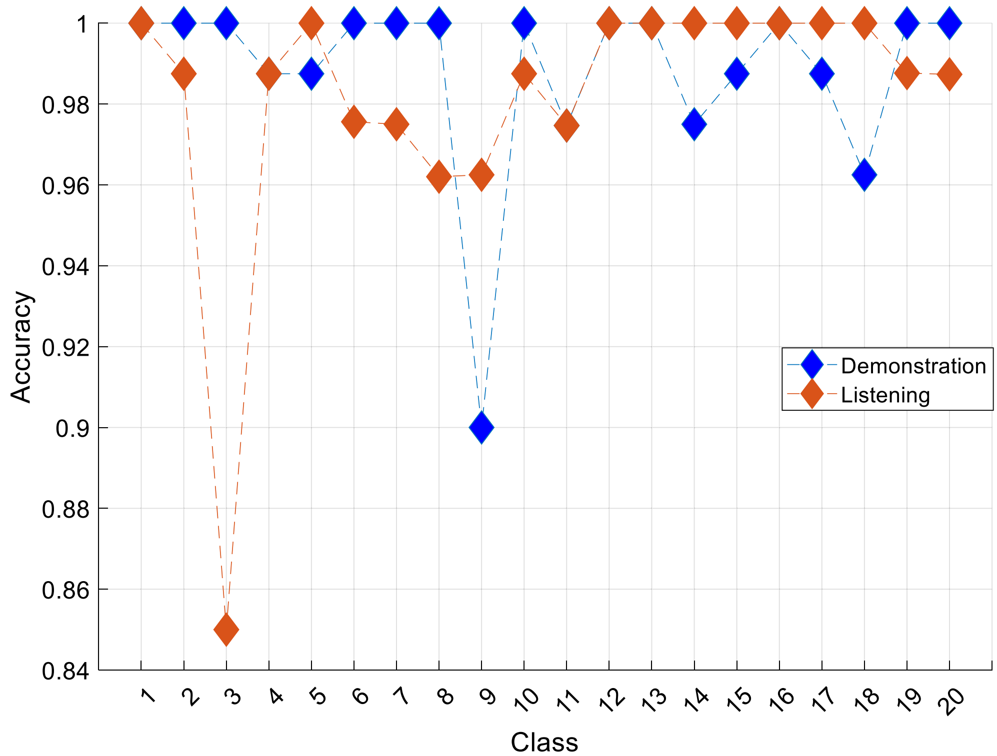

Fig. 11. Accuracy the twenty classes (Turkish sentences) in the dataset by experiment mode.

Table 4
Channel-wise accuracies (%) of the proposed model and other methods.

Method	Demonstration-based EEG dataset (Channel 8)	Listening-based EEG dataset (Channel 7)
Statistics	85.34	78
Local Binary Pattern	50.70	54.13
Local Ternary Pattern	51.99	53.98
Hamsi Pattern	71.76	75.98
Twine Shuffle Pattern	73.01	80.97
Proposed Model	94.69	95.25

- The TSEEG dataset consists of twenty Turkish sentences, which is the native language of the volunteers. Therefore, the experiments may need to be duplicated using sentences collected in other languages.
- We used pre-determined hyperparameter settings for the kNN and SVM classifiers used in the model. These hyperparameters can be further refined to optimize the classification results.

7. Conclusions

The majority of EEG datasets for text and speech recognition are not publicly available, and there is a shortage of EEG sentence datasets in the literature. This study acquired the TSEEG dataset to develop our model and classify sentences from EEG signals. The dataset acquired from a group of volunteers is automatically distinguished with very high performance using our proposed method with demonstration and listening modes. Our classification model is computationally lightweight and has two new methods—DSBP and IMCMV for textural feature extraction and iterative result voting. The model attained 98.81 % and 98.19 % overall accuracy rates in the demonstration and listening modes, respectively, with the TSEEG dataset. These favorable results indicate that our proposed DSBP-IMCMV-based EEG signal classification model may be implemented for sentence classification for brain-computer interface applications. In future works, we intend to validate our results using larger datasets in multiple languages. Furthermore, this work will facilitate the development of EEG-based communication devices, improving non-verbal communication for persons with speech or sensory disabilities. Also, our model's DSBP-based feature engineering and IMCMV based voted result generation are highly versatile and can be applied to the classification of other physiological signals.

Funding

This research is supported by the 121E399 project fund provided by the Scientific and Technological Research Council of Turkey (TUBITAK).

CRediT authorship contribution statement

Prabal Datta Barua: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Tugce Keles:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Sengul Dogan:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization. **Mehmet Baygin:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Turker Tuncer:** Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Caner Feyzi Demir:** Conceptualization, Validation, Writing – original draft. **Hamido Fujita:** Conceptualization, Validation, Writing – original draft. **Ru-San Tan:** Conceptualization, Validation, Writing – original draft, Writing – review & editing. **Chui Ping Ooi:** Conceptualization, Validation, Writing – original draft, Writing – review & editing. **U. Rajendra Acharya:** Conceptualization, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The processed data required to reproduce the above findings are available to download from https://www.kaggle.com/datasets/mehmetbayin/turkish-sentence-eeg-dataset.

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