Brain-Computer Interface based on Neural Network with Dynamically Evolved for Hand Movement Classification

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***Abstract*— Translating brain commands into movements on the prosthetic robot is not an easy task. It is needed a control system for the prosthetic robot based on human body signals to predict the desired movement so that the robot is part of the body. This assistive device is used to help people with disabilities perform functional movements such as gripping with motor activities performed on all five fingers. This paper proposed a hand movement recognition system based on electroencephalogram (EEG) using the Neural Network with Dynamically Evolved Capacity (NADINE). The data generated from the model test shows almost the same value as NADINE, with a maximum accuracy of 98% and an average prediction time of 14 milliseconds. These results further strengthen that the NADINE model can be used in real-time.**

Keywords*— *Electroencephalography, NADINE, hand movement.

I. INTRODUCTION

According to data recorded in the journal Agroindustrial Accident, 2020, the agricultural sector tends to be more prone to physical accidents. According to data recorded in the journal Agroindustrial Accident, 2020, the number of casualties is 22.8% [1]. The impact is the limitation of activities that affect the work and social standard of living of persons with disabilities [2].

Researchers have begun to develop technologies that can replace lost hands by recognizing the importance of robotic hand tools for amputees who have lost hand organs. The problem is that it is not easy to translate brain commands into movements on the robot arm [3]. Therefore, we need a control system for prosthetic robots based on human body signals to predict the desired movement so that the robot appears as part of the body.

The EEG (electroencephalogram) was first introduced by a doctor in 1875 to reveal the phenomenon of electrical waves in the rabbit brain. Then in 1890, physiologists studied impulse waves in animals. In 1934 EEG sensors began to be used in humans to study the effects of epilepsy, and in 1988 EEG electroencephalographic sensors were oriented to research as a control system [4].

Brain-Computer Interface (BCI) is one of the most popular tools in the world for studying brain waves [5]. The role of artificial intelligence in the field of technology has brought significant changes, especially for control systems on a prosthetic hand. This assistive device is used to help people with disabilities perform functional movements such as gripping with motor activities performed on all five fingers. This motor activity includes functional movements of the thumb, middle, index, ring, and little finger [6].

In principle, motor action detected from brain signals is used for efficient control with an average initiation time of each sub-task of fewer than 3 seconds [7]. In previous studies that supported the use of EEG, the Support Vector Machine (SVM) method was used, among others, to distinguish clamping patterns, with an accuracy of 96 % [8].

A deep learning technique in signal classification has been introduced using a 1D convolutional neural network (CNN). This method uses a motor imaging technique, where participants only need to perform an imaginary model as recorded [9]. The results of this experiment showed an accuracy of 70%. From there, the researchers began to practice the CNN method because this method can process big data very efficiently using multilayer CNN. The accuracy of testing three classes of machine action with images is 74.7% [10]. One of the well-known techniques in data processing is Principal Components Analysis (PCA), which is used to improve classification performance on combinations of CNN features, resulting in an appropriate classifier response [11].

The study of EEG for predicting hand movement is quit interesting. However, the prediction algorithm still has weaknesses in the adaptability of artificial neural networks, such as changes in the signal, object conditions, and sensor durability. As a results, it reduces the effectiveness of EEG usage.

The Neural Network with Dynamically Evolved (NADINE) method was proposed to automatically add and remove network nodes with the drift detection flag [12]. NADINE features such as pruning can cut neurons during training due to the drift. The artificial neural network system has the function of comparing pot weights during reverse propagation.

This paper proposed the implementation of NADINE to recognize a functional hand movement for amputees based on electroencephalogram (EEG).

II. Method

A. Data Selection of Brain Signal

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The five-finger categorical data is used to find patterns in the training system. The synthetic data logging scheme is described in Fig. 1.

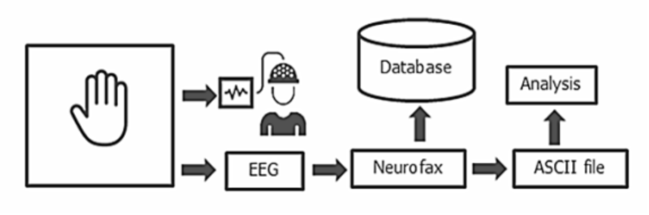

Fig. 1. Synthetic Data Process

The EEG recording mechanism uses a sampling frequency of 200 Hz. Using a bandpass, the signal filter is set in the range of 0.53 -70 Hz. During the data acquisition, the subject must follow instructions to imagine a movement displayed on the screen. The data of imagery movement was recorded for one second. Variable duration pause between movements was 1.5 – 2.5 seconds.

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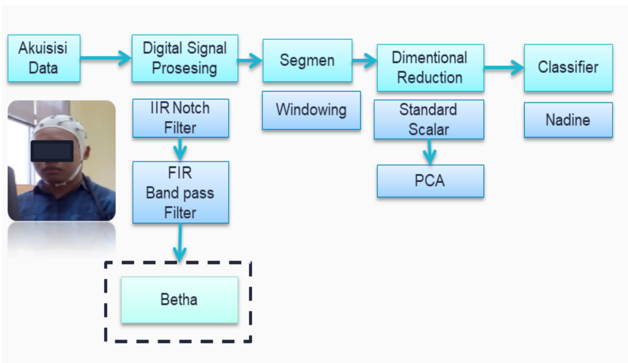

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NADINE provides an automated way to build a DNN from online data streams under a traditional MLP architecture. Developed the width and depth of MLP networks that solve the problem of catastrophic forgetting during online structural development. Adaptive memory and soft forgetting methods have been proposed to specifically address information loss during the addition of a new hidden layer. NADINE can handle regression problems as well as classification problems. It has also been shown that NADINE can extend on-demand network structures and nodes while operating in a fully one-way learning model [20].

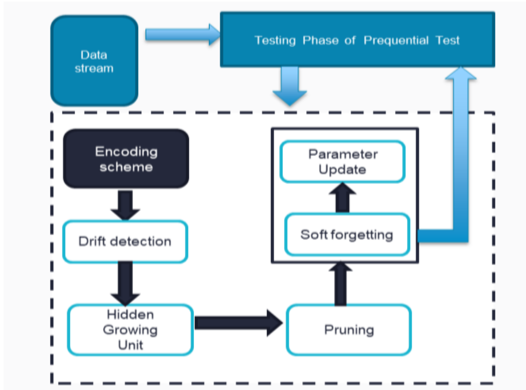

Fig. 3. Nadine

A hidden growing unit is a hidden unit growth determined by the network significance (NS) method. It quantifies the generalizability of the network structure in terms of the statistical contribution under a given probability density function.

Pruning hidden unit strategy was created using the same principles as the hidden growing unit module but based on network distribution rather than network bias. If NADINE suffers from high dispersion and overfitting, it is necessary to reduce network complexity by reducing network complexity. The distribution of the network can be modeled by first deriving the equations E[y2] and E[y]2.

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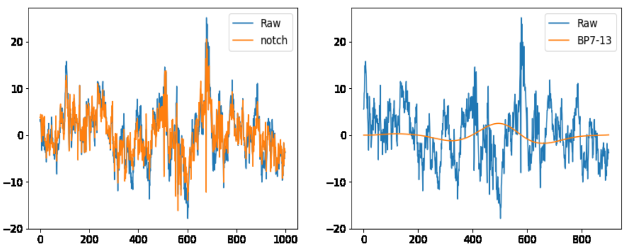
III. Results

A. Testing Result

EEG signal processing includes filtering with noise canceling and signal determination in the motor and sensory domains [14], followed by windowing data segmentation which serves as a time domain multiplier information. Which is very useful for limiting range based on activity. Brain movements tend to be dynamic.



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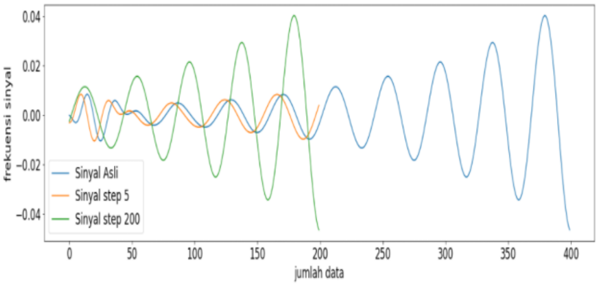

Fig. 5. Windowing

Subsequent window processing with data lengths [15]-[17] from 1 second to 200 data adds additional segmentation to collect additional information about stimulus-responsive activity in the time domain.

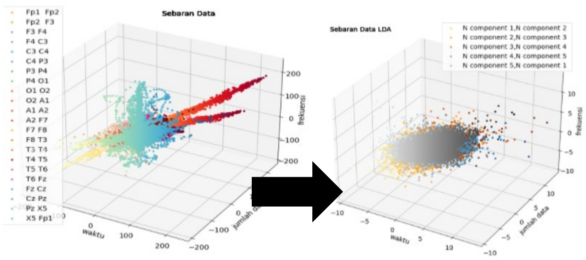

Fig. 6. PCA

It can be seen in the figure that highly correlated or very similar initial matrices are extracted into several different components on PCA with different forms of matrix distribution [18],[19]. After PCA aggregates its predictions into one unit, with this matrix processed, it becomes less but more informative than the previous signal matrix.

TABLE I. TESTING AGAINST EEG DATA 5F.

Respondent	Accuracy	loss	Time
A	97,52	0,0736	0,009
B1	98,66	0,0457	0,008
B2	98,60	0,0478	0,015
F1	98,23	0,0569	0,028
C	98,19	0,0597	0,013
F2	98,51	0,0486	0,011
Average	98,28	0,0554	0,014
Standard Deviation	0,3846	0,0095	0,006

Table 1 shows the testing accuracy across different subjects. The test results show that each respondent has a high accuracy result in the average range of 98.28%, with a deviation value of 0.3% in the model. The results show that the NADINE pattern in each subject can adaptively maintain accuracy in the range above 97 %.

B. *Comparison of Incremental Methods*

Comparative tests against conventional machine learning models are used to emphasize that the test predictions and the underlying framework are correct. In this test, data extraction will also be carried out using RMS. Features will be tested in one parameter. The parameters of various methods are depicted in Tabel 2.

TABLE II. MODEL COMPARATIVE SCENARIO TESTING

Classification	Params
Standard Scalar	***With mean =True , With Std =True***
PCA	***Whiten = True***
MLP	***hidden_layer_sizes=(100), activation='relu',solver='adam', alpha=0.0001, batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5, max_iter=200,shuffle=True, random_state=None, tol=0.0001, verbose=False, warm_start=False,momentum=0.9, nesterovs_momentum=True, early_stopping=False, validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e08, n_iter_no_change=10,max_fun=15000***
KNN	***n_neighbors=5, weights='uniform', algorithm='auto',leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None***
Ada Boost Classifier	***base_estimator=None, n_estimators=50, learning_rate=1.0,algorithm='SAMME.R', random_state=None***
Linear Discriminant Analysis	***solver='svd', shrinkage=None, priors=None,n_components=None, store_covariance=False, tol=0.0001, covariance_estimator=None***
Decision Tree	***Criterion = gini, min samples split=2, min samples leaf=1***

The grid search method was conducted to avoid prediction errors and adding too many predictions. This process divides the data into 80% for training and 20% for testing, which are then imported into the cross-validation data to check the importance of the data. The resultas for the comparison was presented in Table 3.

TABLE III. MODEL COMPARISON SCENARIO TESTING

Model	Mean accuration time	Mean Test accuration (%)	Std Test accuration
Linear Discriminant Analysis	***± 0,002***	***34***	***0,0051***
Ada Boost Classifier	***± 0,051***	***36***	***0,0105***
MLP Classifier	***± 0,011***	***77***	***0,0081***
Decision Tree Classifier	***± 0,002***	***94***	***0,0045***
Kneighbors Classifier	***± 0,173***	***98***	***0,0031***
Proposed Model	***± 0,014***	***98***	***0,0006***

The data generated from the model test shows almost the same value as NADINE with a maximum accuracy of 98% minimum deviation of 0.0006 with an average prediction time of 14 ms. These results further strengthen that the NADINE model can be used in the real-time EEG signal prediction mechanism.

IV. CONCLUSION

This paper presents hand movement recognition using NADINE based EEG signal. The experimental results show that each respondent gives a high accuracy result in the average range of 98.28% with a deviation value of 0.3%. The results show that the NADINE can adaptively maintain accuracy in the range above 97 %. The data generated from the model test shows almost the same value as NADINE with a maximum accuracy of 98% and minimum deviation of 0.0006 with an average prediction time of 14 ms. These results further strengthen that the NADINE model can be used in real-time.

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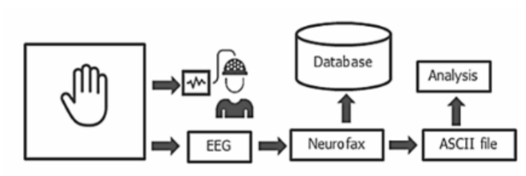

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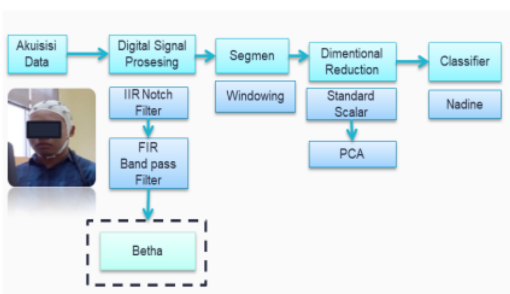

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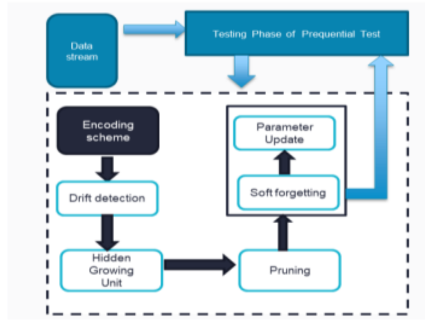

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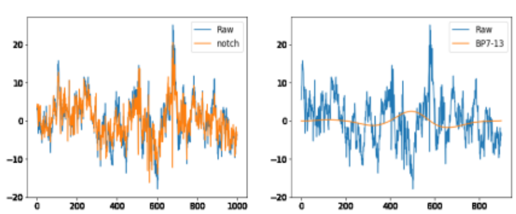

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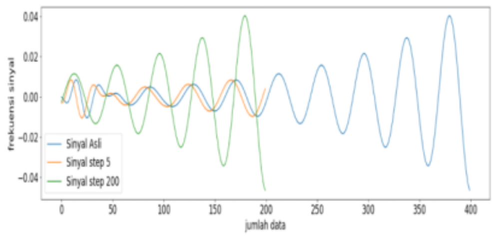

Fig. 5. Windowing

Subsequent window processing with data lengths [15]-[17] from 1 second to 200 data adds additional segmentation to collect additional information about stimulus-responsive activity in the time domain.

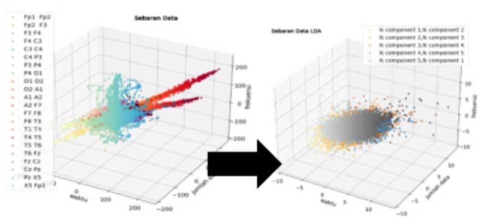

Fig. 6. PCA

It can be seen in the figure that highly correlated or very similar initial matrices are extracted into several different components on PCA with different forms of matrix distribution [18],[19]. After PCA aggregates its predictions into one unit, with this matrix processed, it becomes less but more informative than the previous signal matrix.

TABLE I. TESTING AGAINST EEG DATA 5F.

Respondent	Accuracy	loss	Time
A	97,52	0,0736	0,009
B1	98,66	0,0457	0,008
B2	98,60	0,0478	0,015
F1	98,23	0,0569	0,028
C	98,19	0,0597	0,013
F2	98,51	0,0486	0,011
Average	98,28	0,0554	0,014
Standard Deviation	0,3846	0,0095	0,006

Table 1 shows the testing accuracy across different subjects. The test results show that each respondent has a high accuracy result in the average range of 98.28%, with a deviation value of 0.3% in the model. The results show that the NADINE pattern in each subject can adaptively maintain accuracy in the range above 97 %.

B. Comparison of Incremental Methods

Comparative tests against conventional machine learning models are used to emphasize that the test predictions and the underlying framework are correct. In this test, data extraction will also be carried out using RMS. Features will be tested in one parameter. The parameters of various methods are depicted in Tabel 2.

TABLE II. MODEL COMPARATIVE SCENARIO TESTING

Classification	**Params**
Standard Scalar	***With mean =True , With Std =True***
PCA	***Whiten = True***
MLP	***hidden_layer_sizes=(100), activation='relu',solver='adam', alpha=0.0001, batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5, max_iter=200,shuffle=True, random_state=None, tol=0.0001, verbose=False, warm_start=False,momentum=0.9, nesterovs_momentum=True, early_stopping=False, validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e08, n_iter_no_change=10,max_fun=15000***
KNN	***n_neighbors=5, weights='uniform', algorithm='auto',leaf_size=30, p=2, metric='minkowski', metric_params=None, n_jobs=None***
Ada Boost Classifier	***base_estimator=None, n_estimators=50, learning_rate=1.0,algorithm='SAMME.R', random_state=None***
Linear Discriminant Analysis	***solver='svd', shrinkage=None, priors=None,n_components=None, store_covariance=False, tol=0.0001, covariance_estimator=None***
Decision Tree	***Criterion = gini, min samples split=2, min samples leaf=1***

The grid search method was conducted to avoid prediction errors and adding too many predictions. This process divides the data into 80% for training and 20% for testing, which are then imported into the cross-validation data to check the importance of the data. The resultas for the comparison was presented in Table 3.

TABLE III. MODEL COMPARISON SCENARIO TESTING

Model	**Mean accuration time**	**Mean Test accuration (%)**	**Std Test accuration**
Linear Discriminant Analysis	***± 0,002***	***34***	***0,0051***
Ada Boost Classifier	***± 0,051***	***36***	***0,0105***
MLP Classifier	***± 0,011***	***77***	***0,0081***
Decision Tree Classifier	***± 0,002***	***94***	***0,0045***
Kneighbors Classifier	***± 0,173***	***98***	***0,0031***
Proposed Model	***± 0,014***	***98***	***0,0006***

The data generated from the model test shows almost the same value as NADINE with a maximum accuracy of 98% minimum deviation of 0.0006 with an average prediction time of 14 ms. These results further strengthen that the NADINE model can be used in the real-time EEG signal prediction mechanism.

IV. Conclusion

This paper presents hand movement recognition using NADINE based EEG signal. The experimental results show that each respondent gives a high accuracy result in the average range of 98.28% with a deviation value of 0.3%. The results show that the NADINE can adaptively maintain accuracy in the range above 97 %. The data generated from the model test shows almost the same value as NADINE with a maximum accuracy of 98% and minimum deviation of 0.0006 with an average prediction time of 14 ms. These results further strengthen that the NADINE model can be used in real-time.

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