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Motor Imagery Classifcation using Transfer Learning

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***Abstract*—Brain-Computer Interface has gained significant attention from the research community as it provides a potential avenue to aid people with motor disabilities. However, the major challenge in this is to accurately decode the EEG signals to control an external device. This research study has used EEG data from the participant with spinal cord injury to accurately map them into different classes that can be used as control commands. Further, a deep transfer learning model is implemented to classify motor imagery signals that can be used as control signals for a neuro-prosthetic device. Finally, the proposed method achieves the best accuracy of 100%.**

***Index Terms*—Transfer learning. EEG. Motor Imagery. BCI. Neuro-prosthetics. Machine learning.**

I. Introduction

According to a report by WHO in 2011, 15% of the world's population lives with some form of disabilities and around 2 to 4% has significant motor disabilities. This number translates to around 150 million [1]. People with these difficulties face issues of self-dependence, quality of life, low confidence, etc. Considering the severity of these issues, assistive devices have been suggested to improve the quality of life for people with disabilities by giving them their independence and confidence [2]. Several studies have tried to work in the field of assistive living from different dimensions, ranging from computer science to human factors to mechanical engineering to neuroscience, etc. Some of these works have been realized on an industrial scale such as the hand of hope, etc. [3]. One of the important dimensions for research in assistive devices is to utilize brain activation for different purposes. This type of system of utilizing brain activation or signals to control an external device is called the Brain-Computer Interface (BCI). Brain-Computer Interfaces or BCIs has been an active area of research since the 1970s when the first BCI was developed at the University of California [4]. A typical BCI uses brain signals that can be recorded invasively using electrodes placed inside the brain or non-invasively using brain imaging techniques such as EEG, fMRI, etc. EEG or Electroencephalography has been one of the most commonly used brain imaging techniques for a BCI because of its portability, non-invasiveness, inexpensive price, good temporal resolution, etc. However, there are some downsides of using EEG as well, for instance, bad signal to noise ratio, bad spatial resolution, presence of irrelevant artefacts, etc. Nonetheless, it has been widely accepted and used for BCI research and other research work [5]. In the case of people with motor disabilities such as hemiparesis or post-stroke disabilities (Hemiplegia) or paraplegia or even in a locked-in state, the brain is still functional which can be used to control assistive devices. The most common use case is Motor Imagery (MI), where a voluntary motor movement is simulated in the brain. Several studies have shown that this type of simulated motor movement is very similar to actual motor movement [6]. This extant functionality has been utilized in several studies on assistive devices. Conventionally, relevant and discriminative features would be extracted which would be used to train a classifier and then the classifier would classify signals into respective classes. This is how the brain activity would be classified using machine learning algorithms.

Pfurtscheller introduced EventRelated Desynchronisation and Synchronisation (ERD/ERS) in 1999 [7]. Since then, ERD/ERS in the alpha (8–13 Hz) and beta bands (14–25 Hz) method, has been become one of the most commonly used techniques in BCI research and are one of the most commonly used features in motor execution (ME) and MI [8] [9]. Other methods rely on feature engineering techniques, where a set of features would be extracted that would have sufficient discriminative capacities to accurately differentiate between two classes. In study [10], statistical features such as interquartile range, median absolute deviation, and energy have been used to classify imagined and executed hand movements using EEG signals. They reported the best accuracy to be 97% . In another study, authors have tried to detect epileptic seizures using EEG signals. To accurately classify EEG data related to the seizure, the authors used feature engineering and linear discriminant analysis. They proposed using innovative use of features such as Gini's coefficient to extract features and used a relatively basic Linear discriminant analysis-based method to effectively categorize seizure data with a 100% accuracy [11]. Other studies have used different signal processing and feature engineering techniques to accurately classify different EEG signals ranging from sleep quality to seizure activity [18], [30], [31].

In this study, the focus is on motor imagery classification. In [12], a method was conceived to classify motor imagery signals. The signals were first transformed into wavelets using discrete wavelet transform and then a subset of these wavelets was selected based on the desired frequency range. After

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which, statistical features were extracted and ranked using Gini's coefficient. The combination of different ranked features was classified using random forest. The best accuracy achieved in the study was 85%. In another study [13], we compared different machine learning methods on the same dataset. We had, instead of using a very complex wavelet transform of signals, implemented a simple FIR bandpass filter to filter-in the desired frequency signal. The best accuracy that we found in the study was 70% using SVM based method.

In the last couple of years, however, there has been a shift towards deep learning approaches instead of using feature engineering, which requires domain expertise and is very time-consuming. In this paper, we are exploring the use of transfer learning as a method instead of using traditional machine learning techniques to accurately decode EEG signals. These traditional machine learning models rely heavily on domain-specific knowledge, for example selecting the features for motor imagery tasks that would be discriminative enough to produce good classification accuracy. This type of exercise requires sufficient domain knowledge before selecting any features. However, using a deep transfer learning approach democratize the field. Also, using a transfer learning approach instead of building a deep learning model from scratch has added benefits such as it requires less training time, working sufficiently well with low data, and producing better performance [26]. Therefore, in this study, we have implemented a deep transfer learning model – ResNet-50 for decoding EEG signals. These decoded signals will be used as control signals for a neuroprosthetic device.

The main contributions of this paper are as follows:

1) Decoding of EEG signals recorded from a subject with paralyzed limbs.
2) Successfully implementing a transfer learning-based method pre-trained over images to the classification of raw EEG signals.
3) Achieving significantly better classification accuracy (100%) than the state of the art methods in decoding EEG signals using transfer learning.

This paper is structured with the introduction as its first section where the ideas that are used in this study and their contexts have been provided. A short review of the relevant literature is introduced as a subsection to the introduction, followed by a description of data used in this study in section II. Section III, showcases the methodology and the architecture of our model used in this study. In section IV, the results have been presented, followed by a discussion on the results, conclusion, and future direction in the consequent section.

II. Related Literature

A. Transfer Learning and BCI

Deep learning has recently become hugely popular after it has achieved near human-level or in cases even better capabilities in detecting objects in images. Deep learning attempts to learn features from mass data either by unsupervised algorithms or by semi-supervised algorithms. They conventionally were being used for image-based data but recent successes in domains such as audio or text classification, have made them an attractive venue for researchers in other domains such as in EEG classification. The charm of deep learning, along with achieving better classification accuracy, is learning of features without supervision or with semi-supervision. This is in contrast with traditional machine learning approaches where the researchers would extract relevant features manually depending on their knowledge of the subject. Several unique deep learning algorithms for EEG-based BCI have been proposed in recent years [14]. Many of them use CNNs (convolutional neural networks). A deep CNN architecture is described by [15], which combines elements of temporal and spatial convolution filters for their first convolution-pooling block and three more convolution-pooling blocks to further reduce dimensionalities before feeding the output to a fully-connected layer. To decrease the learnable parameters and decouple the relationship inside and across feature maps, the shallower architecture EEGNet presented by [16] uses separable convolution instead of convolution-pooling blocks. A multi-band, multi-channel EEG input encoding to the deep CNN is proposed by [17]. However, it's highly dependent on data and requires a large amount of data for proper training. In the case of images or audio, this type of data creation is relatively easier than EEG data creation, where a subject is needed to produce mass data. To overcome, these issues related to deep learning methods, transfer learning approaches have been introduced [18]. Transfer learning is a concept of applying knowledge learned in the source domain to help the learning capabilities of a model in the target domain. In this approach, a model that is pre-trained on a different dataset is used to do a different task for a different dataset. It has gained ample attention from researchers working in the field of BCI or EEG. Several studies have tried to employ deep transfer learning methodologies for their tasks. The authors in the study suggested Manifold Embedded Knowledge Transfer (MEKT) construct projection matrices that minimize the joint probability distribution shift between the source and destination domains using a combination of alignment, feature extraction, and domain adaption algorithms [19]. Other studies have tried to implement adversarial neural networks for representation learning. Using the adversarial learning method, they tried to learn the subject invariant features which they then fed into the deep learning model of EEGNet and shallow ConvNet [15] [16] [20]. The authors of [20] have employed autoencoder along with adversarial networks to learn subject invariant features from EEG data and compared the results with other methods and a baseline CNN based model. They reported the best accuracy for EEG classification using to be 73%. In another study [18], the challenge of inter-subject variability in EEG was addressed by developing five schemes of deep CNN model developed by [15]. These schemes were categorised based on the number of parameters it needs to be optimised on. The best accuracy reported in this study was 84.19% (±9.98%) for two-class motor imagery classification. In the study [27], a complex pipeline was developed using discrete wavelet transform to filter EEG signals and then employing continuous wavelet transform to convert EEG signals into images. These EEG images were input to different transfer learning models and the best accuracy reported was 95.71%. Another study [27] reported their classification accuracy to be 66.36% using the transfer learning approach. In this study, we have implemented a deep transfer model based on ResNet-50 on EEG data [21]. Similar to studies [15], [18], [27], we wanted to explore the efficiency of using a CNN based deep learning model for non-image data classification. Therefore, based on the survey of literature on the transfer learning approach to time-series data, a ResNet-50 model was selected to be used as a transfer learning approach [29]. The model has also been used in various computer vision problems as the state-of-art model. Our hope in using this model is that we would be able to achieve similar results in the study as well.

III. Data Used

The data used in this study came from [22]. The data consists of a single subject's EEG recordings. The subject had a high spinal cord lesion and was using an exoskeleton (brain-neural computer interface) to operate a paralyzed limb. The cue-based BNCI paradigm consisted of two tasks: 'imagination of movement' of the right hand as Class 1 and 'relaxation/no movement' as Class 2, see Figure 1. A randomly displayed visual signal is utilized to inform the subject when to open (for the Green square) and when to close (for the Red Square). These two indications were provided 24 times in total, with inter-trial intervals (ITIs) of 4-6 seconds between them. The device was driven back to the open position after each indication was presented for 5 seconds. It took one second to reset the exoskeleton to the open position. Using an active electrode EEG system (Acti-cap® and BrainAmp®, BrainProducts GmbH, Gilching, Germany) with a reference electrode placed at FCz and a ground electrode placed at AFz, EEG was recorded from 5 conventional EEG recording sites F4, T8, C4, Cz, and P4 according to the international 10/20 system. EEG was recorded at a 200 Hz sampling rate, bandpass filtered between 0.4 and 70 Hz, then pre-processed with a tiny Laplacian filter.

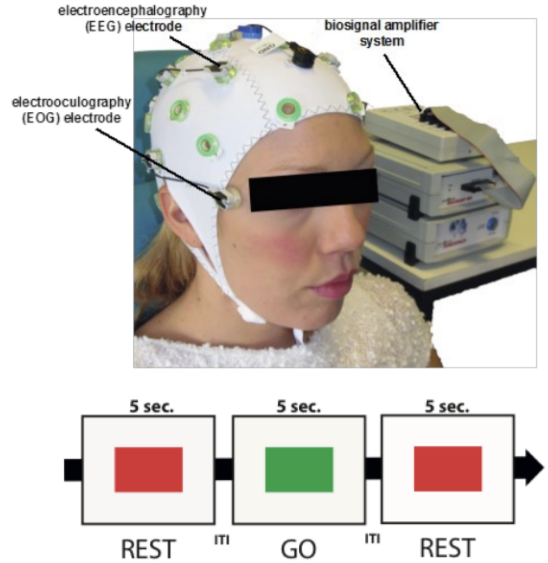

Fig. 1. Showing (a) recording of EEG with a participant to control a neuro-prosthetic device, (b) the timing scheme of the experimental paradigm.

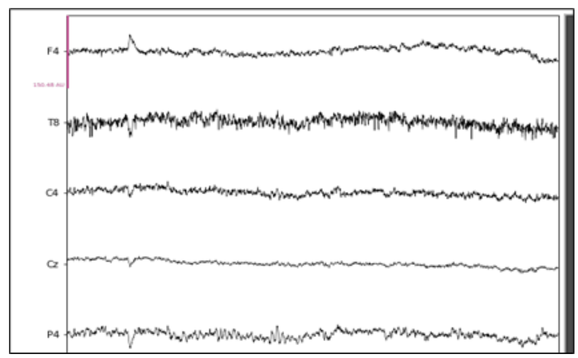

Fig. 2. Showing raw EEG waveform of the data.

IV. Methodology

A. Notations

Let denote the dataset, where Xi, Yi denotes the raw EEG signal at the i^{th} trial for channels 'c' and discrete-time 't'. Similarly, 'Y_i' corresponds to the class label for the i^{th} trial. Using a transfer learning approach, where the aim is to use learned parameters from the source Domain 'D_i' to help the learning capabilities of the method in the target domain, 'D_t'. In this study, a transfer learning model of resnet-50 has been used to decode the EEG signals into control signals for controlling neuro-prosthetics.

B. Data Preparation

The data used in this study is created by [22]. It consists of EEG recordings recorded over a subject with paralyzed limbs for different tasks. To acquire information about Motor Imagery, the data was processed and filtered. While recording EEG, several noise elements are stored, ranging from line frequency interference to undesirable artefact signals, see Figure 3., which shows line frequency artefact. All of these could impede the classification progress of the model. As a result, before proceeding with the analysis, these noise elements and undesired signals need to be removed. The brain's normal motor output channels are linked to a variety of electrophysiological features for example mu and beta rhythms correspond to motor imagery signals. Mu rhythm has been found in the frequency range of 7-13 Hz in several investigations. The mu (8-12 Hz) and beta (13-30 Hz) rhythms are two of the most important aspects [23]. Therefore, based on these considerations, an FIR bandpass filter was realized to

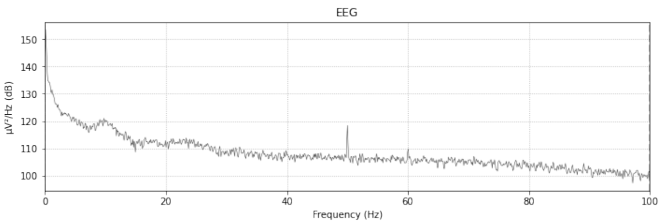

Fig. 3. Showing power spectral density of a raw EEG signal.

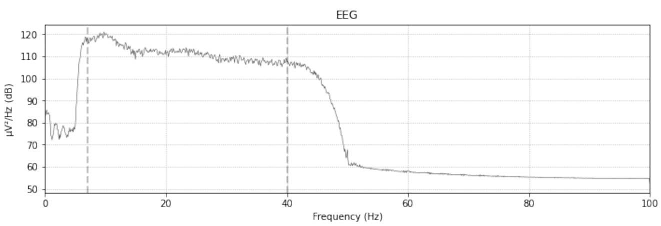

Fig. 4. Showing power spectral density of the FIR bandpass filter realized for the frquency range of 7 to 40 Hz.

filter out the undesired frequencies. The filter was designed for the frequency range of 7 to 40 Hz with Hamming window of 0.0194 passband ripple and 53 dB stopband attenuation. The filtered EEG signals was one dimension (1D) time-series and the ResNet model require the input to be an image-based data. Other studies have tried to circumvent this issue by taking the spectrogram of the signal or by projecting EEG signals into a 3D shape using other methods [24], [25]. One of the main objectives of this study was to keep the pre-processing stage to a minimum. Therefore, we have not used any of the signal transformation techniques that are commonly used for converting EEG 1D signals into images such as short-time frequency transform or continuous wavelet transform, etc. [27]. In this study, we simply reshaped the 1D EEG into a 3D tensor of shape [35 × 35 × 3] and input it into the model. The tensor shape is so chosen because of the constraint of the transfer learning model - it can only accept input shape which is greater than [32 × 32 × 3]. Therefore, to achieve a closest shape to this tensor an 19 second time-window was developed. Since, the sampling rate of the data used in this study is 200 Hz and the window size was of 19 seconds, 3800 samples were taken in each loop. After which these samples were reshaped into the tensor of size [35 × 35 × 3]. There were a few samples there were being dropped using this method. This whole process was repeated till the end of EEG recording. In this way, a single EEG image has been produced. The same process has been followed for the whole EEG data. Our approach with this method is to make use of simple raw EEG data for classification which would reduce the reliance on domain expertise for EEG signal processing by reducing the pre-processing stage.

C. Model Architecture

The model used in this paper is based upon ResNet-50 [21]. The lowest layers have been changed from the original model to accommodate the new data tasks requirement. The model has been used in many computer vision problems. It has 4 convolution blocks after which the fully connected layers, SoftMax layer and output layers have been added to learn features inherent to this data. The model utilised weights of the model trained on ImageNet, so the model did not learn the low-level features on this data. These added Fully connected layers have been used for fine-tuning the model for this dataset. Below is the architecture of the model used in this paper.

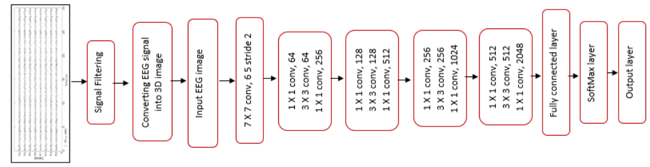

Fig. 5. Showing transfer learning model architecture that is based on ResNet-50 [21]

V. Result

The model has been fine-tuned using Stochastic Gradient Descent optimizer with a learning rate of 0.01 and for 10 epochs. The pre-trained model (ResNet-50) was trained on ImageNet and those weights have been used in this study as well to learn ow level features. Further Fully connected layers have been added to fine-tune the model on this data to classify the two EEG classes, see Figure 4. The function that has been used to calculate loss in this method was categorical cross entropy loss. Table I., shows the model summary that includes the shape of different layers as well as the parameters. The total trainable parameters in this model were only 4098. Since the weights used in this model were pre-trained, this has reduced the training time and computation cost a lot. In that sense, it is relatively easier to implement and train on this data as well. To evaluate the performance of the method used in this study, classification accuracy has been calculated. This metrics was chosen as all the studies that our method has been compared against have used such a metric.

1) Classification Accuracy: It is defined as the number of correct predictions that are made out of total predictions. Mathematically,

$$Accuracy = \frac{TruePositive + TrueNegative}{TotalSample} \times 100\% \quad (1)$$

In Table II., a comparison of classification accuracy from different studies that have been done on this dataset has been shown and reported. This method achieves outperformed all the reported methods on this dataset. The table also reports the classification accuracy of EEG signals by the authors who created this dataset. The accuracy reported here is the accuracy by which their model was able to control an external device i.e. neuro-prosthetic device. Figure 5., shows the training and

TABLE I
MODEL SUMMARY

Layer Type	Output Shape	No. of Parameters
ResNet-50	(None, 2048)	23564800
Flatten layer	(None, 2048)	0
Dense layer	(None, 2)	4098
Trainable params: 4,098		

TABLE II
COMPARISON OF ACCURACY OF THIS WORK WITH OTHER WORKS ON THE SAME DATA.

Research Studies	Witkowski M, et al., (2014)	Hashmi A., et al (2021) (a)	Hashmi A., et al (2021) (b)	This work
Classification Accuracy	*60.9±19.76%*	*85%*	*70%*	*100%*

validation loss and accuracy of the model. Table III shows a comparison of classification accuracy from different studies which have used the transfer learning method for EEG classification. The method used in this study has outperformed all other methods that have employed transfer learning approach and achieves a classification accuracy of 100%.

VI. DISCUSSION AND FUTURE WORK

In this study, a transfer learning model was implemented for EEG signal classification, corresponding to two tasks – imagining of the opening of hand and relaxation. Our main objective was to develop a deep transfer learning method to accurately decode EEG signals. Along with that, we wanted to develop a model that reduces the dependence of EEG decoding on pre-processing stage (or domain expertise), which is a major challenge in most EEG classification studies. In this study, we got a very good classification accuracy of 100% using a transfer learning model while not relying heavily on the pre-processing stage. We have compared the performance of our method in two ways – by comparing it with studies on the same dataset (Table II) and with the studies that have used the Transfer learning method (Table III). In Table II, we have compared our results with other studies on the same dataset. The data used in this study was collected using EEG signals recorded with a participant with spinal cord injury. The experimenters asked the participant to imagine the movement of the hand for the given cues. These signals were then used to operate a neuro-prosthetic device. They

TABLE III
COMPARISON OF CLASSIFICATION ACCURACY WITH OTHER TRANSFER LEARNING METHODS

Research Studies	Classification Accuracy
[28]	66.36%
[20]	73%
[18]	84.19 (±9.98)%
[27]	95.71%
This Study	**100%**

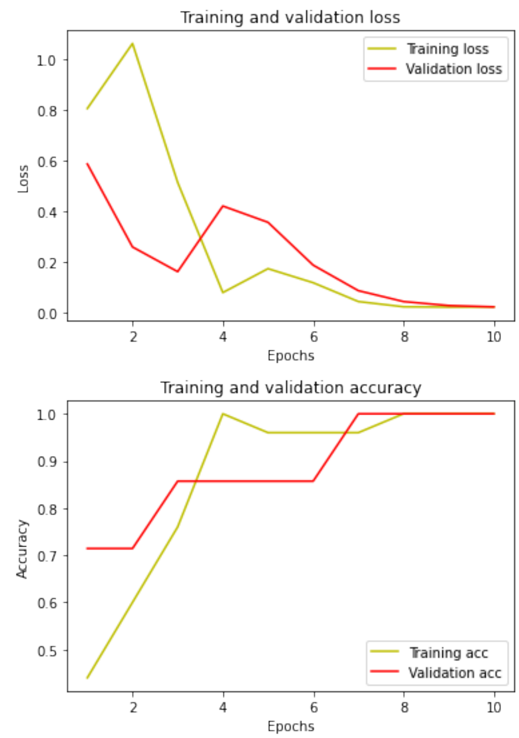

Fig. 6. The figure shows the model's training and validation loss and accuracy on the data.

reported their performance accuracy to be 60.9 ± 19.76%. To get the best performance accuracy, they even made use of EOG signals along with EEG signals [22]. The accuracy reported in [22] is not of EEG classification but rather the accuracy of their model's ability to control the external device by taking EEG signals as input. To improve their controlling accuracy even further, they made use of EOG signals along with EEG signals. In another study [12] on the same data, the authors had primarily focused on signal processing techniques to improve classification accuracy. The signal was transformed using a discrete wavelet transform. Then, only specific wavelet components were selected based on the desired frequency range. After which, statistical features such as median absolute deviation inter-quartile range, etc. were extracted. These features were ranked and different combinations of these features were compared against each other to see the improvement in classification accuracy. After employing such a complex and fine-tuned method, the best-reported accuracy was found to be 85%. In the follow-up study [13], the authors have tried to reduce the reliance of their model on the different signal processing techniques to improve the adaptability of their method. The signal was bandpass filtered using an FIR filter. Then, relevant features were extracted from the filtered signal. These features were then compared using different machine learning techniques for the classification task on the same dataset. The best accuracy reported was 70% using the SVM method.

In Table III, we have compared our method with other studies that have used transfer learning methods for EEG classification. In this study, we employed a transfer learning approach for the same classification task. This method has achieved a classification accuracy of 100% with a minimal data pre-processing stage. This method, therefore, has the potential to be used in other EEG databases with similar task contexts. In table 2., we have provided a comparison between the results of this study and other studies. In [28], the authors have tried a binary classification of motor imagery signals. They reported the best framework for such a problem is a combination of different fine-tuned transfer learning models with EEGNet. The best classification accuracy reported in the paper is 66.36%. A similar approach has been followed by [18] where the authors developed different schemes based on a CNN transfer model and compared them against a baseline model (simple CNN trained from scratch). The best accuracy reported was in the range 84.29 (±9.98)%. In [20], a new method of representational learning using adversarial networks was proposed. The authors suggested that subject invariant representation can efficiently be learned through the use of conditional variational autoencoder along with an adversarial network. The authors demonstrated their method on EEG data and reported the best accuracy to be 73%. The study [27] developed a more complex scheme where first the EEG signals were filtered using discrete wavelet transform and then converted into time-frequency EEG images using continuous wavelet transform. After which the converted EEG images were input to a deep transfer model and produced the best accuracy of 95.71%. In this study, however, we have tried to minimize the dependence of our method on pre-processing technique. A certain level of pre-processing was still needed to produce good enough results. We bandpass filter the EEG signals after which it was reshaped along with five channels into a 3D tensor which was input into the ResNet-50 model. The model produced the best accuracy of 100%. In terms of accuracy, this model has outperformed all other studies performed on this dataset and studies that have used transfer learning.

The major drawback of this study is that the proposed method may only work with EEG datasets created with similar task contexts. This dimension can be further explored in the future by implementing this method on other benchmark EEG datasets with similar task designs. Other drawbacks associated with this study are that since the data is recorded over a person with paralyzed limb therefore the data is very limited – to a single subject. To further validate our method, therefore, we would be implementing this method on a larger dataset in the future.

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