

# Can Pre-Trained Convolutional Neural Networks be used as Feature Extractors for Video-based Neonatal Sleep and Wake Classification?

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## Research note

**Keywords:** Convolutional neural networks (CNN), Video electroencephalogram (VEEG), Neonatal sleep, sleep and wake classification, feature extraction

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# Abstract

## Objective

In this paper, we propose to evaluate the use of a pre-trained convolutional neural networks (CNN's) as a features extractor followed by the Principal Component Analysis (PCA) to find the best discriminant features to perform classification using support vector machine (SVM) algorithm for neonatal sleep and wake states using Fluke® facial video frames. Using pre-trained CNN's as feature extractor would hugely reduce the effort of collecting new neonatal data for training a neural network which could be computationally very expensive. The features are extracted after fully connected layers (FCL's), where we compare several pre-trained CNN's, e.g., VGG16, VGG19, InceptionV3, GoogLeNet, ResNet, and AlexNet.

## Results

From around 2-h Fluke® video recording of seven neonate, we achieved a modest classification performance with an accuracy, sensitivity, and specificity of 65.3%, 69.8%, 61.0%, respectively with AlexNet using Fluke® (RGB) video frames. This indicates that using a pre-trained model as a feature extractor could not fully suffice for highly reliable sleep and wake classification in neonates. Therefore, in future a dedicated neural network trained on neonatal data or a transfer learning approach is required.

## Introduction

Sleep is an essential behavior for the development of the nervous system in neonates [1–3]. Normally, newborn babies sleep between 16 to 18 hours per day. Continuous sleep tracking and assessment could potentially provide an indicator of brain development over time [4–5]. To achieve this, automatic sleep and wake analysis is required, which can offer valuable information on a neonate's mental and physical growth, not only for healthcare professionals but also for parents [6].

Currently, Video electroencephalogram (VEEG) is considered as a gold standard for neonatal sleep monitoring, which requires a number of sensors and electrodes attached to a neonate's skin to collect multiple-channel EEG signals [7–9]. In addition, the use of VEEG is labor-intensive, where human effort on annotating sleep states is required [10]. Therefore, one would demand a contact-free sleep monitoring system for neonates. In recent years, unobtrusive or contact-free approaches have gained a lot of attention for sleep monitoring [11–16]. All these methods are more successful in adults [17] [18]. In contrast, video-based methods appear to be a promising approach, since it is more comfortable and convenient to use both in the home or in the hospitals [19] [20]. With the advancements in deep learning algorithms and clinical research on neonatal facial patterns [21] [22] a new, unobtrusive approach of monitoring sleep patterns has been proposed [23] [24]. However, evaluation of the deep learning models demand big database to train the prediction model.

The main contributions of this work include: (a) extracting features from Well-known CNN's e.g., VGG-16, VGG-19, InceptionV3, GoogLeNet, ResNet, and AlexNet, (b) comparing different color palette (amber, high contrast, red-blue, hot metal, and grayscale) from RGB and thermal video frames, and (c) evaluating the extracted features using PCA followed by SVM to classify neonatal sleep and wake classification. As this was an explorative study, to evaluate the feasibility of pre-trained model as features extractor to classify neonates' sleep and wake states using video frames, we started with a small pilot study population of neonate's video frames data by adopting a robust and less computational complex approach to classify sleep states.

## Methods

### Subject Database

Video and VEEG data from seven neonates were collected retrospectively by a pediatrician at the Children's Hospital affiliated to Fudan University, Shanghai, China [25]. The detailed descriptions of the demographics and physical conditions of neonates is shown in Additional file 1: Table S1. Annotation of sleep and wake states was performed by a professional neurologist on each 30-sec VEEG epoch and video frames respectively according to American Academy of Sleep Medicine (AASM) [26].

### Intensity-Based Detection

To enable identifying sleep and wake states for neonates using video frames, it is required to have precise face detection in Fluke@video [27]. Detail description of Intensity-based detection has been discussed in our previous paper [25]. Figure 1 shows the input video frame, and neonatal facial region is detected using intensity-based method. After that the detected face region is mapped on other color palettes of the video frames to extract the facial region.

### Pre-trained CNN models

Our proposed method is to classify neonatal sleep and wake states using pre-trained CNN. As each layer of the CNNs output act as an activation unit for the input images. As initials layers capture basic input images features like spots, boundaries, and colors pattern that are inattentive by the deeper hidden layers to form complex higher-level features pattern to present a better-off image illustration [28]. Literature studies reveal that while using pre-trained CNNs for feature extraction, the features are usually extracted from the FC layers right before the final output classification layer [29] [30]. Considering this motivation, we extracted the features from fully-connected (FC) layers of pre-trained network. The details descriptions of all the pre-trained model has been mentioned in Additional file 1: Table S2.

### VGG16 and VGG19 Model

VGG model [31] contains a stack of convolutional layers followed by three fully-connected layers (FCL). In this work, we used both pre-trained VGG16 and VGG19 models, and features were extracted from the last three FCLs.

## **AlexNet Architecture**

The architecture of AlexNet [32] that contains a total of eight layers. In this work, we extracted features from the last two FCLs of the pre-trained AlexNet.

## **ResNet-18**

The baseline structure of residual network (ResNet) [33] is the same as the other CNN's, except that a shortcut link is added to each pair of  $3 \times 3$  filters. To classify neonates sleep and wake states, we extract 1000 features from the last FCL of pre-trained ResNet-18 model.

## **GoogLeNet**

GoogLeNet [34] have unique features that help them to achieve the state-of-the-art results and outperforms other previous networks, e.g.,  $1 \times 1$  convolution is used as a dimension reduction to reduce computation usage. In the work, we have used the pre-trained GooLeNet network and features are extracted from the last "FC1000" layer.

## **InceptionV3**

Inception-v3 is the factorization idea in the third iteration of GoogLeNet [35]. The last FCL is used to extract the features from the pre-trained Inception-V3 model to perform neonate's sleep and wake classification.

## **Principal Component Analysis (PCA)**

PCA is a method to differentiate the discriminants features in the dataset by suppressing variations [36]. In this paper, once the features are extracted from FCLs of CNN's, we input these features to PCA to find the best discriminated features, to help SVM to classify neonates sleep and wake states at the next stage.

## **Support Vector Machine (SVM)**

Based on features extracted from the pre-trained CNN's, we employed SVM classifier to classify neonatal sleep and wake states [37–38]. We have used the "classificationLearner" app in Matlab R2018b with the SVM default setting (kernel function='linear', box constraint = 1 )to perform the classification.

## **Results And Discussion**

Twenty-two experiments were conducted on RGB and thermal videos respectively. For evaluation purposes, all the results are expressed in terms of sensitivity(Se), specificity(Sp), precision(p), and accuracy(Ac), obtained using five-fold cross-validation, The result are validated with the VEEG annotations.

Table 1 shows the sleep and wake classification results obtained by the SVM classifier after feature extraction using different pre-trained CNN's. We observed that the overall performance of using FCL6-7-8 in VGG-16 and VGG19, FCL8 in AlexNet, and FCL layer in inceptionV3, ResNet-18 and GoogLeNet was low when used to classify neonatal sleep and wake states. Multifarious statistical results obtained via SVM to classify neonatal sleep and wake states shows disproportionate pattern. However, RGB-InceptionV3 (FCL) shows the best values for Se is 97.4%, but Ac drop to 55.1%, similarly RGB-VGG16 (FCL8) and RGB-VGG19 (FCL8) shows Se of 90.0%, but overall accuracy is drop to 66.2% and 65.2% respectively. However features extracted from AlexNet (FCL7) trained via SVM shows the best optimal results with an Ac of 65.3%, Se 69.8%, and Sp of 61.0% to classify neonate's sleep and wake states. In contract to the other features extracted values from pre-trained networks, features extracted from AlexNet (FCL7) contains discriminant features, that assist SVM to classify neonate's sleep and wake stage. One of the main reason to achieved higher statistical results using pre-trained AlexNet is that as pre-trained AlexNet was originally trained on just over a million images as compared to other CNN 's that were trained on more the 15 million images, depicts more complex features architecture values at different fully connected layer [39] [31]. It is observed that in AlexNet the first layer has filter of size  $11 \times 11$  and the second layer has  $5 \times 5$  filter and so on, there is no standard about filter sizes and max pooling. The convolutions for each layer are decided purely experimentally. In contrary to that, other CNN have standard protocol such as in VGG-Net all the convolution kernels are of size  $3 \times 3$ , max-pooling is done after 2 or 3 layers of convolutions. GoogLeNet work on parallel combination of  $1 \times 1$ ,  $3 \times 3$ , and  $5 \times 5$  convolutional filters. The overall complex nature of pre-trained CNN's distinguished AlexNet to obtained better performance to classify neonate's sleep and wake stages. Figure 2a shows the standard deviation of all the sleep and wake features extracted from AlexNet FCL7. It is observed that most of the sleep and wake extracted features from FCL7 are lies almost in the same region. However AlexNet shows slightly better performance than other extracted features using SVM, one of the main reason is that the corresponding trained features are quite separated from each other. Figure 2b depicts the standard deviation of discriminant corresponding features extracted after PCA from pre-trained AlexNet (FCL7). These discriminant AlexNet (FCL7) features help to achieve better neonate's sleep and wake classification accuracy as compared to other pre-trained CNN's.

Table 1

Neonatal sleep and wake classification results (five-fold cross-validation) using different pre-trained CNN's combined with an SVM classifier.

Video Frame			<i>Se%</i>	<i>Sp%</i>	<i>Ac%</i>	<i>P%</i>
			<b>SVM</b>			
RGB	VGG16	FCL6	52.4	64.05	58.3	57.7
		FCL7	52.6	75.1	64.3	66.5
		FCL8	40.9	<b>90.0</b>	66.2	40.2
Thermal		FCL6	73.1	40.16	58.4	60.2
		FCL7	72.4	40.3	58.1	60.0
		FCL8	71.2	41.5	58.0	60.1
<b>RGB</b>	<b>AlexNet</b>	<b>FCL7</b>	<b>69.8</b>	<b>61.0</b>	<b>65.3</b>	<b>62.7</b>
Thermal		FCL7	61.0	40.4	49.9	55.0
RGB		FCL8	59.5	71.2	65.7	64.7
Thermal		FCL8	56.5	60.0	58.4	52.7
RGB	VGG19	FCL6	81.9	36.4	52.6	54.6
		FCL7	81.0	36.1	51.9	54.5
		FCL8	40.9	<b>90.0</b>	65.2	<b>79.4</b>
Thermal		FCL6	63.6	54.2	57.1	63.2
		FCL7	67.6	45.0	54.6	60.3
		FCL8	62.1	52.4	58.1	61.8
RGB	InceptionV3	FCL	<b>97.4</b>	30.0	55.1	52.5
Thermal		FCL	67.3	47.6	58.7	61.4
RGB	ResNet-18	FCL	73.2	50.8	61.2	58.2
Thermal		FCL	66.7	46.7	58.3	60.8
RGB	GoogLeNet	FCL	77.7	41.8	55.3	55.5
Thermal		FCL	66.6	46.7	57.83	60.8
<p>*true positive (TP) = VEEG depict sleep and correctly identified as sleep by our feature extraction approach, false positive (FP) = VEEG depict awake and incorrectly identified as sleep by our feature extraction approach, true negative (TN) = VEEG depict awake and correctly as awake identified our feature extraction approach, false negative (FN) = VEEG depict sleep and incorrectly identified as awake by our feature extraction approach</p>						

As a proof of study, we have analyzed other neonatal facial color palettes extracted from Fluke® SmartView. Additional file 1: Table S3 shows the statistical results achieved using multiple color palettes such as amber, high contrast, red-blue, hot metal, and grayscale. In contrast to the results shown in Table 1 Fluke® multiple colors palette depict disproportionate results such as high contrast-AlexNet (FCL8), InceptionV3-Hot-metal (FCL), GoogLeNet-Grayscale(FCL) and VGG19-Red-Blue (FCL6) achieved the best values for Se are 84.8%, 76.3%, 73.0% and 81.1% respectively. Similarly VGG-19-Amber (FCL) shows the best values for Sp is 87.8%. However overall Ac obtained from these colors palates are quite low, VGG19-High Contrast (FCL7) shows the best Ac of 65.6%. One of the main reason is that the range of these Fluke® color palettes are quite narrow as shown in Additional file 1: Figure S1.

In general, the results of our proposed feature extraction approach using pre-trained CNN's to classify neonatal sleep and wake states are modest [20]. The main reason for using the feature extraction approach is that it doesn't demand a lot of computational capacity and it is quite robust as we do not need to retain the network or even its layers, these attributes compel us to start with feature extraction approach to classify neonatal sleep and wake states, however, experimental analysis depict that this approach doesn't offer the promising result to act as an aided tool for clinicians to classify neonates' sleep and wake states unobtrusively. One of the cause of attaining such modest accuracy is that the all the existing pre-trained CNN's network were trained on natural images such as animals, flowers, sceneries, and automobiles etc. The feature patterns of pre-trained CNN's networks classes are quite different from our neonate's database, that makes it difficult for existing pre-trained networks to classify neonate's sleep and wake sates [40] [41]. However, as there is no such unobtrusive sleep and wake, neonatal studies has been reported in the literature by analyzing the neonate's facial pattern using the features extraction approach. This research could be helpful for future studies to adopt other techniques (e.g., transfer learning or dedicated CNN) to classify neonatal sleep and wake states using video frames to achieve better accuracy.

## Conclusions

This work experimentally verifies the achievability of unobtrusive neonate's sleep and wake states via automatic classification using video frame from fluke® camera. Five-fold cross-validation depicts the modest accuracy of 65.3% from pre-trained AlexNet at FCL7, compared with VEEG annotated data by a neurologist for sleep and wake states. In the future, the transfer learning approach/dedicated CNN's and more datasets collection with different ethnic groups will be the next step of our research work.

### Limitations of the study

It is also important to note that this is a preliminary study, where video data collection took place in a controlled environment with fixed camera placement, stable lighting conditions, and under the supervision of neonatal nurses and pediatricians. Furthermore, as for this proof-of-point study, we analyze the variations in neonatal facial pattern with no sleep-related issues. The accuracy concerning to



those with sleep syndromes have remained unclear. This article focus only on two-state (sleep and wake) states, dedicated design of neonatal deep learning architecture to classify neonate's sleep staging is on the foremost next step of this research work.

## Abbreviations

Fully-connected layers(FCL's), Video electroencephalogram (VEEG), convolutional neural networks (CNN's), Principal Component Analysis (PCA), support vector machine (SVM)

## Declarations

**Author Contributions:** Conceptualization, approach, software, justification, formal analysis, imagining, script—inventive manuscript preparation, M.A.; examination, resources, database curation, writing—inventive manuscript preparation, review and editing, C.C and C.W.; writing—inventive manuscript preparation, review and editing, X.L.; writing—inventive manuscript preparation, review and editing, B.Y; VEEG data collection and subject management, C. L; data annotation, X.W, clinical database and subject health condition, L. W.

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**Competing interests:** The authors declare no conflict of interest.

**Availability of data and material:** At this point the data used in this paper cannot be shared or released to a third party.

**Consent for publication:** Written informed consent to publishing is obtained from parents of all the subjects by the pediatrician at Children's Hospital of Fudan University, Shanghai, China.

**Ethics approval and consent to participate:** The study protocol was designed according to the hospital's clinical study regulation and approved by the Internal Ethics Committee for Neonatal experiments of Children's Hospital of Fudan University, Shanghai, China. All participants were consent to participate in the data collection process. Written informed consent was obtained from the involve for publication of

this research article and any accompanying images and videos. A copy of the written consent is available for review by the Editor of this journal.

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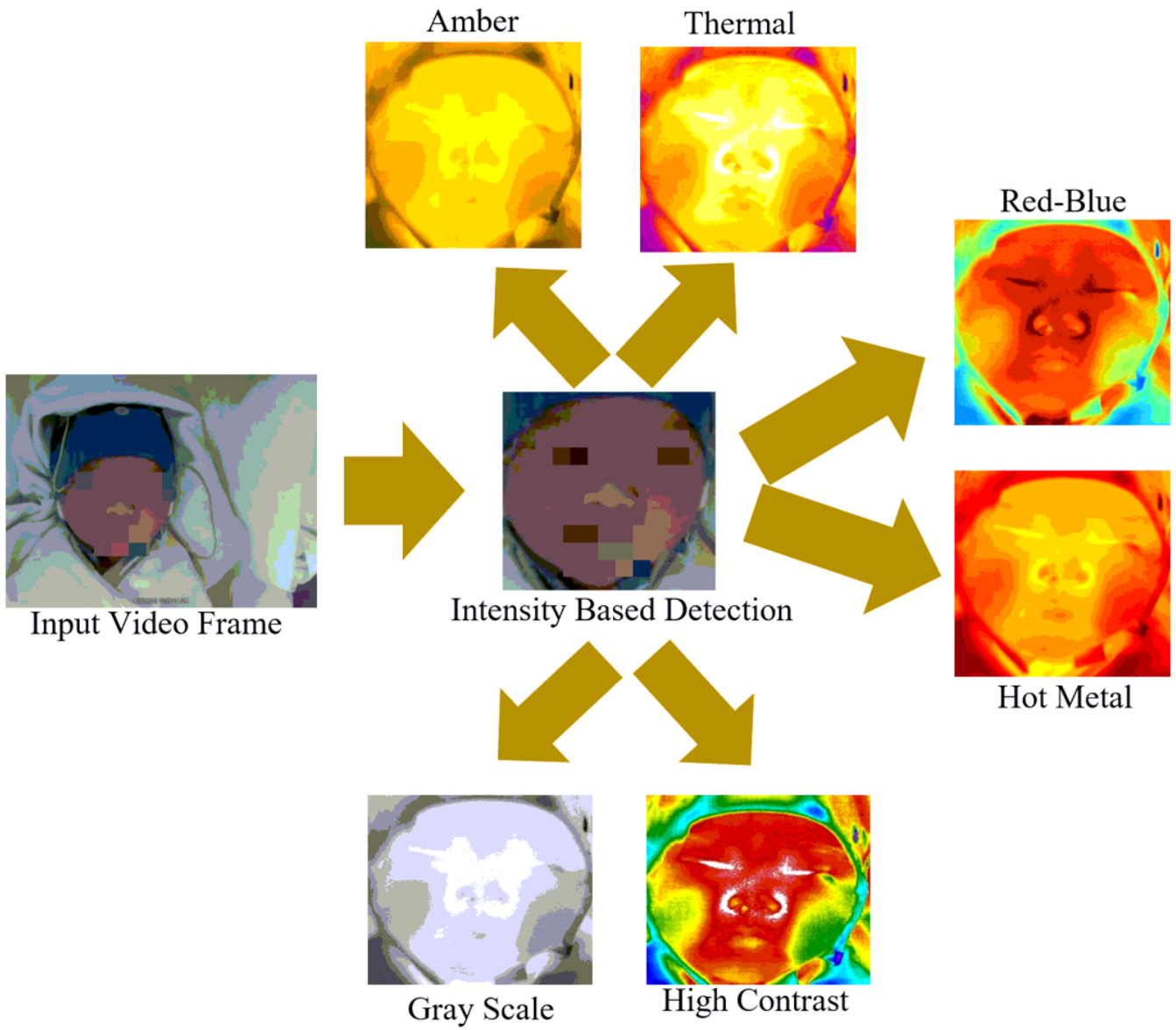
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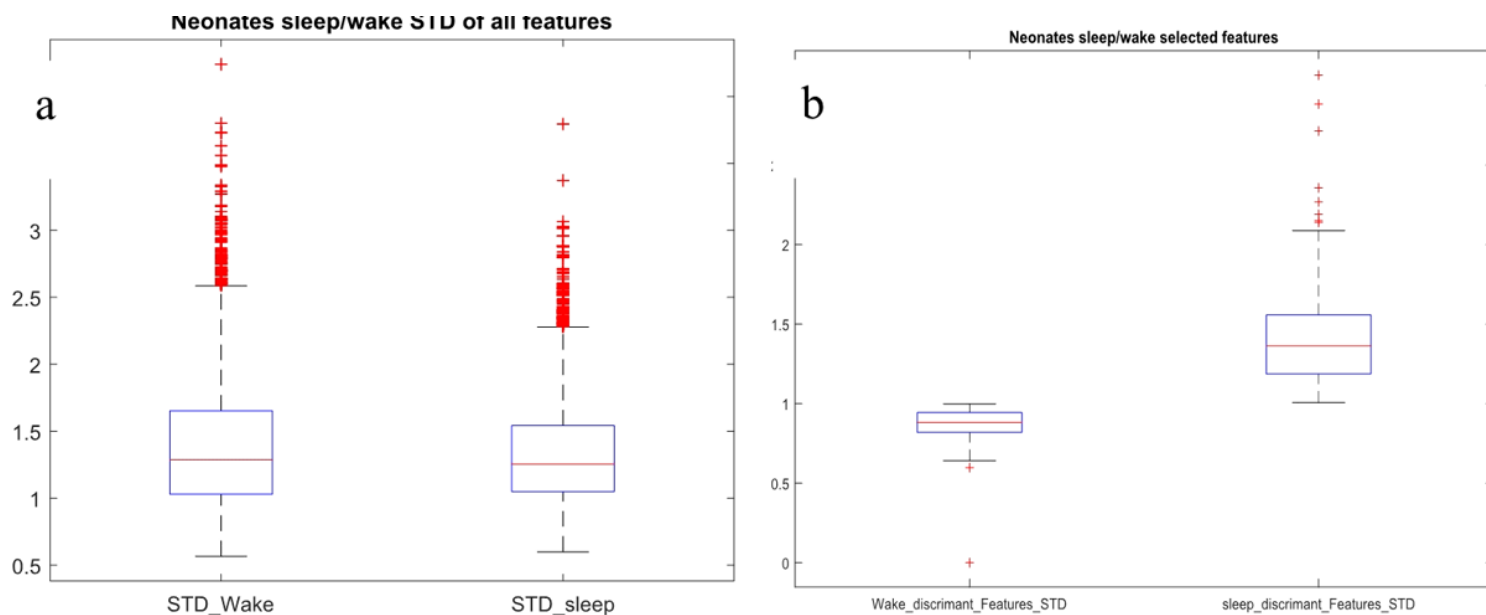
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## Figures



**Figure 1**

Neonatal face detection using the intensity-based detection method.



**Figure 2**

a) Overall features extract from pre-trained AlexNet (FCL7). b) Discriminant corresponding features extracted (STD) from pre-trained AlexNet (FCL7).

## Supplementary Files

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