A novel Deep-Learning model for Human Activity Recognition based on Continuous Wavelet Transform

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Abstract

Human Activity Recognition (HAR) has recently become in the spotlight of scientific research due to the development and proliferation of wearable sensors. HAR has found applications in such areas as digital health, mobile medicine, sports, abnormal activity detection and fall prevention. Neural Networks have recently become a widespread method for dealing with HAR problems due to their ability automatically extract and select features from the raw sensor data. However, this approach requires extensive training datasets to perform sufficiently under diverse circumstances. This study proposes a novel Deep Learning - based model, pre-trained on the KU-HAR dataset. The raw, six-channel sensor data was preliminarily processed using the Continuous Wavelet Transform (CWT) for better performance. Nine popular Convolutional Neural Network (CNN) architectures, as well as different wavelets and scale values, were tested to choose the best-performing combination. The proposed model was tested on the whole UCI-HAPT dataset and its subset to assess how it performs on new activities and different amounts of training data. The results show that using the pre-trained model, especially with frozen layers, leads to improved performance, smoother gradient descent and faster training on small datasets. Additionally, the model performed on the KU-HAR dataset with a classification accuracy of 97.48% and F1-score of 97.52%, which is a competitive performance compared to other state-of-the-art HAR models.

Keywords 1

Human activity recognition, biomedical signal processing, transfer learning, continuous wavelet transform, convolutional neural network

1. Introduction

Human Activity Recognition (HAR) is of particular interest due to its growing role in such areas as health care (especially for the elderly and patients with limited mobility), sports, abnormal activity recognition, fall prevention, epileptic seizure detection and military training [1, 2, 3]. HAR has become especially relevant with the spread of intelligent clothing items, such as smartwatches, fitness bracelets and smartphones, which usually contain diverse built-in sensors and auxiliary devices (accelerometers, gyroscopes, magnetometers, GPS sensors, cameras, microphones) [4]. By combining the computing power of these devices and their ability to interact with the outside world, HAR opens up a vast field for applications, for example, real-time human activity monitoring, physical training evaluation, burn calories counting, detecting falls and recognizing anomalous activity for people with neurological disorders.

Usually, the construction of HAR models based on wearable sensors includes the following steps: signal pre-processing and noise removal, feature extraction and feature selection to obtain representative characteristics, and further use of sophisticated Machine Learning (ML) algorithms for activity classification [5, 6]. In many publications, the approach with manual feature extraction and

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selection has shown promising results [7, 8, 9, 10], although this approach has certain drawbacks. The major limitation is that statistical signal characteristics (i.e., shallow features) are often insufficient to recognize complex, multi-step activities and transitory states, due to which models based on the classical approach are often rather complex. In addition, the usage of this approach requires high qualifications of the researcher and an individual approach for each dataset.

A promising approach to solving HAR problems is Convolutional Neural Networks (CNNs). Due to the possibility of automatic construction and selection of features, CNNs can obtain high-level characteristics and often show better results than classical methods [11, 12, 13, 14]. Despite the proven performance of CNNs, they require extensive training datasets to produce adequate results on new data. Otherwise, this method is prone to underfitting and overfitting problems. There are several techniques to mitigate this problem, such as regularization and data augmentation [15, 16]. Another widely-used approach is Transfer Learning (TL), where a model trained on one (source) dataset is fine-tuned on another (target) dataset [17].

While there are many models pre-trained on data for visual object recognition [18], this work focuses on developing a pre-trained model specifically for the HAR classification problem. The resulting model will make it possible to train deep CNN on relatively small HAR target datasets, transferring the knowledge obtained from the more extensive and general source dataset.

2. Employed datasets and Prior works

In this work, we used two time-domain HAR datasets, one of which is relatively new. The Khulna University Human Activity Recognition dataset (KU-HAR) [19][30] was chosen for pre-training, and the University of California Irvine Human Activities and Postural Transitions dataset (UCI-HAPT) [8][31] for fine-tuning and testing. This section provides brief information on these datasets and the main works where they were used.

2.1. KU-HAR Dataset

For model pre-training, the KU-HAR dataset was used [19]. It was published in 2021 and contains 20,750 non-overlapping time-domain subsamples belonging to 18 classes (stand, sit, talk-sit, talk-stand, stand-sit, lay, lay-stand, pick, jump, push-up, sit-up, walk, walk-backward, walk-circle, run, stair-up, stair-down and table-tennis).

Each subsample has a duration of 3 seconds and consists of six channels. The data was collected from 90 participants aged 18 to 34 using a smartphone attached to the waist. The recorded signals contain raw data from a triaxial accelerometer and a triaxial gyroscope with a sampling frequency of 100 Hz. Gravitational acceleration was discarded during data acquisition, and no denoising and filtering operations were performed. It can be claimed that KU-HAR is a realistic (representational) dataset as it is an unbalanced dataset with no denoising operation performed and with no overlapping between samples.

In [19] and [20], the authors used manual feature extraction and feature selection methods and the Random Forest classifier, which resulted in the classification accuracy of 89.67% and 89.5% on the KU-HAR dataset, respectively. Authors of [7] used Wavelet Packet Transform and Genetic Algorithm, with the subsequent use of tree-based classifiers, which resulted in maximal accuracy of 94.76%. In [13], using a sequential CNN model and transforming raw signals into circulant matrices, the authors achieved a classification accuracy of 96.67% for this dataset.

2.2. UCI-HAPT Dataset

The UCI-HAPT dataset [8] and its subset were used as a benchmark for the proposed pre-trained model. This dataset was published in 2014 and is an extended version of the University of California Irvine Human Activity Recognition dataset (UCI-HAR) [21], supplemented with postural transitions. The UCI-HAPT contains tri-axial accelerometer and gyroscope signals collected with a waist-mounted smartphone with a sampling frequency of 50 Hz. The data was collected from thirty volunteers aged from 19 to 48 years. It contains sensor data for 12 classes (walking, walking upstairs, walking downstairs, sitting, standing, laying, stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie, and lie-to-stand), 6 of which do not belong to the KU-HAR dataset. The signals were pre-processed for noise removal using median and low-pass Butterworth filters.

Authors of [22, 23, 24] achieved promising classification results for the UCI-HAPT dataset. However, in this work, we did not use the proposed frequency domain variables but extracted samples from the raw sensor readings. It was done due to the requirement of Transfer Learning that target and source samples should have the same shape.

3. Methodology

In this work, we kept to the following workflow: first, the row signals samples were pre-processed using the CWT with different wavelet and scale values. After that, nine popular CNN models were trained on the generated scalograms, and the best-performing combination of the model architecture and CWT parameters was selected. The chosen, pre-trained model was then fine-tuned on the target datasets, and the results were compared with the non-pre-trained one. Detailed descriptions of the carried-out steps are provided in the subsections below.

3.1. Continuous Wavelet Transform

Continuous Wavelet Transform (CWT) of a function $x(t)$ is a mathematical operation defined by the following expression:

$$X_{\omega}(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{+\infty} x(t)\bar{\psi}\left(\frac{t-b}{a}\right) dt, \quad (1)$$

where $\psi(t)$ is a continuous function in the frequency and time domain called a mother wavelet, a is the scale value, $a > 0, a \in \mathbb{R}^{+*}$, and b is the translational value, $b \in \mathbb{R}$. The overline represents the operation of the complex conjugate.

Results of the CWT can be represented as a heat map (i.e. scalogram) with the b-values set along the x-axis, a-values set along the y-axis, and the intensity of each point determined by (1). An example of a transformed accelerometer x-axis signal from the KU-HAR dataset is illustrated in Figure 1.

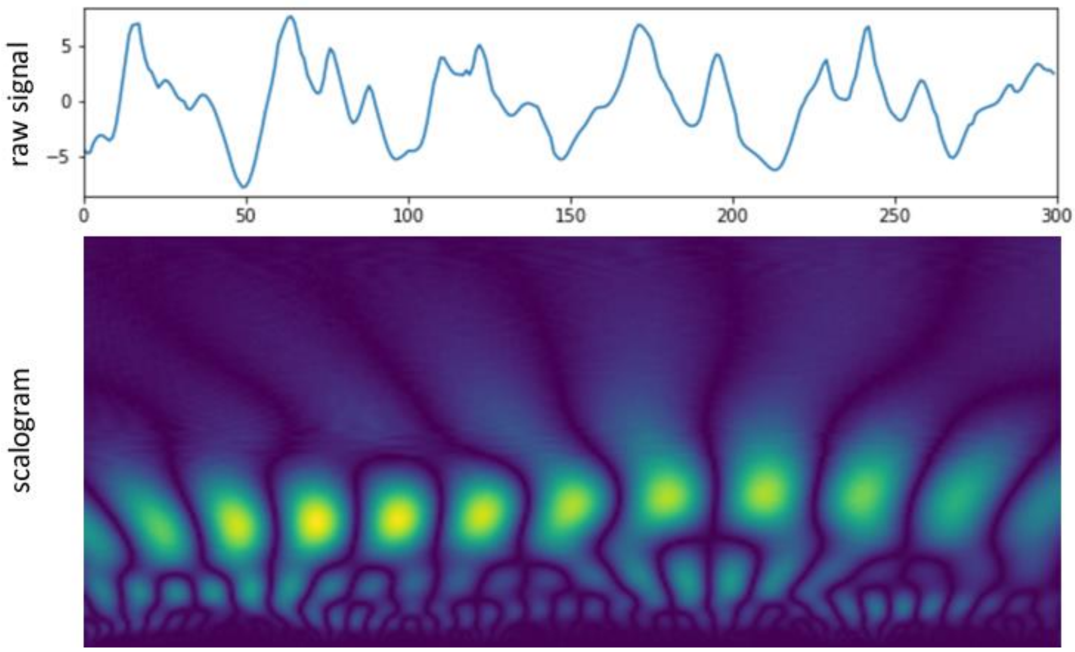

Figure 1: A transformed accelerometer x-axis signal (scalogram). Morlet wavelet, $a \in (0, 128]$

The Wavelet Transform (WT) has certain advantages over the commonly-used Fourier transform. First, it provides a better representation of functions with sharp breaks and peaks, which often are important signal characteristics in HAR problems. Secondly, it has the ability to obtain both temporal and local spectral information, overcoming the problem of the non-stationary nature of signals. Therefore, it is more efficient to replace the Fourier-related transforms with the WT, which is a powerful tool for frequency and time domain feature extraction.

Authors of [25, 26, 27, 28] achieved promising performance using CWT together with CNNs for time-series classification problems. Additionally, it is considered that CNNs with 2-D convolutional layers, in general, produce better results than the same neural networks with 1-D convolutional layers when classifying signals from wearable sensors.

In this paper, we have used CWT-generated scalograms to improve the accuracy of the models and mitigate the overfitting and underfitting problems that often occur during fine-tuning the pre-trained models. The scalograms were generated using the Mexican Hat and Morlet wavelets with the a values from 0 to 32, 64, 128 and 256. Thus, the models' performance was tested on eight different CWT configurations.

3.2. Model selection

In order to select a CNN model nine popular architectures were tested, namely ResNet50, ResNet101, ResNet152, Xception, InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169 and DenseNet201. All mentioned models were trained on all scalogram configurations, which resulted in 72 possible combinations. Each input sample consisted of 6 scalograms (a scalogram for each signal channel). It is important to note that Xception, InceptionV3, and InceptionResNetV2 architectures have restrictions on the input data shape, so the scalograms with a values less than 128 could not be used. Hence, the total amount of tested combinations is 60.

Each combination was attempted five times to avoid sub-optimal local minima, which resulted in 300 models being trained. The criteria for the model selection was classification accuracy.

3.3. Model testing

The selected pre-trained model was tested on scalograms generated from the pre-processed UCI-HAPT dataset. This dataset contains sensor reading for 12 activities, 6 of which are entirely new for the pre-trained model (i.e. the source dataset does not include instances of these classes). The CWT parameters for the target dataset were chosen to be the same as for the selected model.

3.3.1. Target dataset pre-processing

To perform fine-tuning, the target dataset was pre-processed to have the same sample shape as the source dataset. Firstly, the sampling frequency of the raw sensor readings was doubled from 50 Hz to 100 Hz. It was done by insertion of the average value between two adjacent readings. After that, samples from the pre-processed data were extracted using the non-overlapping windowing technique with a 3-second sample duration, resulting in 4847 six-channel samples in the target dataset.

We used the whole UCI-HAPT dataset and its subset to determine how the pre-trained model performs on different target dataset sizes. The subset contains 30% of randomly selected samples from the original dataset, which stands for 1652 samples. Figure 2 illustrates the datasets' distributions.

As can be noticed from Figure 2, both the UCI-HAPT dataset and its subsets are imbalanced. Moreover, considering that the signals in the UCI-HAPT were pre-processed using median and low-pass Butterworth filters and that the frequency of signals was artificially adjusted, it can be claimed that source and target datasets have substantial distinctions in signal representation. It implies that if the selected model performs a Positive Transfer on the UCI-HAPT dataset, it would be reasonable to use the proposed pre-trained model for other signal data with similar distinctions, which would be helpful, for example, for Cross-Position Activity Recognition (CPAR).

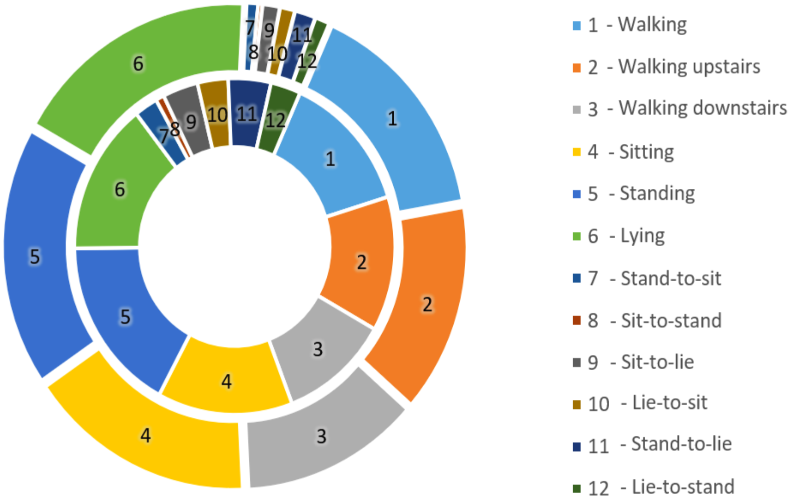

Figure 2: Class sample ratios of the pre-processed UCI-HAPT dataset (outer circle) and its subset (inner circle).

3.3.2. Transfer learning

To perform Transfer learning and assess the selected model, the top fully connected layer of the pre-trained model was removed and replaced with a new one with weights set using the Xavier uniform initialization. The number of neurons in the new fully connected layer corresponds to the number of classes in the target dataset (in our case, 12). The model performance was tested with different numbers of frozen layers.

Layer freezing (i.e. making some layers non-trainable) is a technique widely used in Transfer Learning. The number of layers to freeze is usually chosen according to the similarity between the source and target datasets. If the datasets are similar, it may be sufficient to freeze all layers except the fully connected top layer of the network. The more diverse the datasets are, the more layers of the pre-trained network need to be trainable during fine-tuning.

The numbers of frozen layers were chosen to correspond to the architecture of the selected model, which is DenseNet121 (discussed in a later section). The DenseNet121 comprises a conv block, four dense blocks and a fully connected layer. Hence, the following configurations were considered: only the top fully connected layer is trainable, the first 308 layers are frozen (conv, dense 1, 2, 3 blocks frozen), first 136 layers are frozen (conv, dense 1, 2 blocks frozen), and all layers are trainable. The described approach is illustrated in Figure 3.

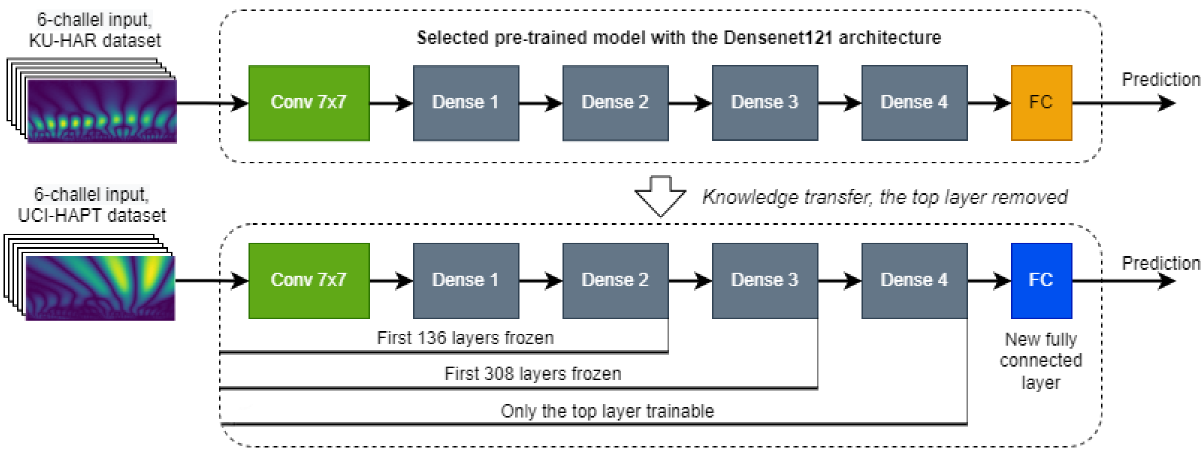

Figure 3: Transfer learning using the selected pre-trained model.

4. Results and discussion

In this section, the experimental results obtained using the methods represented in the previous section are described.

First, we describe the selected combination of CNN architecture and CWT parameters that performed the best on the KU-HAR source dataset. Second, the selected pre-trained model is assessed on the scalograms created from the pre-processed UCI-HAPT dataset and its subset. The model performance with different amounts of frozen (i.e. non-trainable) layers were tested to estimate how their presence affects the results for target datasets of various sizes.

We used randomly selected 70% of the datasets for training and 30% for testing. For validation, 10% of the training sets were used. It has been experimentally determined that 100 epochs are sufficient for training most models, although this number could have been increased to 120 if underfitting was observable. Adam was chosen as the optimizer; the learning intensity was set to 0.001. Loss function - categorical crossentropy.

4.1. Selected pre-trained model

We tested nine popular architectures, namely ResNet50, ResNet101, ResNet152, Xception, InceptionV3, InceptionResNetV2, DenseNet121, DenseNet169 and DenseNet201. Each of the 60 combinations was attempted five times to avoid sub-optimal local minima, which resulted in 300 models being trained. The criteria for the model selection was classification accuracy.

It was found that the best results were produced by the model with DenseNet121 architecture and the following CWT parameter values: Morlet wavelet and scale from 0 to 256. This combination resulted in significant classification accuracy of 97.48% and F1-score of 97.52% on the KU-HAR source dataset. The confusion matrix of the conducted classification using the selected model is illustrated in Figure 4.

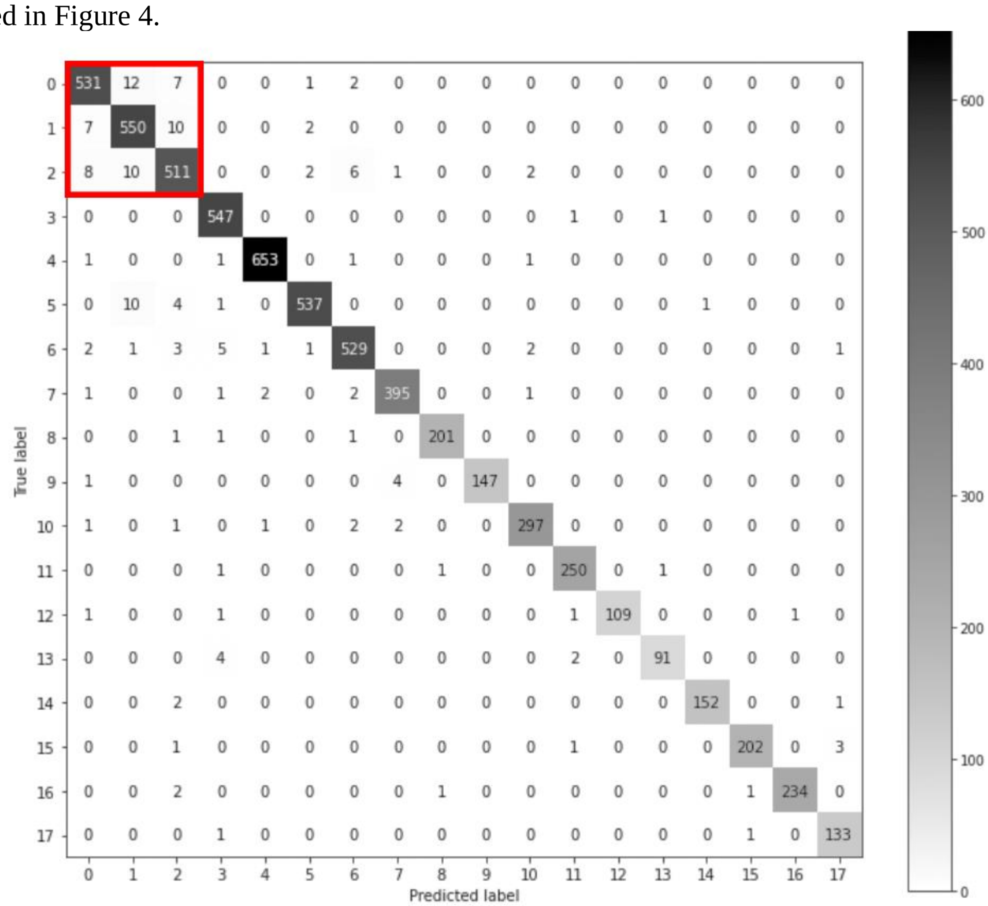

Figure 4: Confusion matrix of the classification of the KU-HAR dataset using the selected model.

As could be noticed from Figure 4, the agglomeration of classification errors is a square with classes stand, sit and talk-sit, which are all static activities. These activities are challenging to differentiate, and they can be considered separately to improve performance, which is a promising direction for further research.

The F1-score value, which is not affected by the dataset imbalance, is reasonably close to the classification accuracy value, implying the reliability of the classification performance of the selected model.

Considering the fact that the KU-HAR is an unbalanced dataset with no denoising operation performed (i.e. a realistic dataset), we find the performance of the proposed pre-trained model rather promising. Table 1 provides a comparison of the results achieved on the KU-HAR dataset in recent works.

Table 1
Comparison of the results achieved on the KU-HAR dataset in recent works

Study	Accuracy (%)	F1-score (%)
[20]	89.5	80.67
[19]	89.67	87.59
[29]	-	94.25
[7]	94.76	94.73
[13]	96.67	96.41
Proposed	**97.48**	**97.52**

As could be seen from Table 1, the proposed model outperforms most state-of-art works, where the KU-HAR dataset was used, which indicates the effectiveness of the selected model, as well as the potency of the approach with using CWT and CNN for the HAR classification problems.

4.2. Performance on the target dataset

We used the whole UCI-HAPT dataset and its subset to determine how the pre-trained model performs on different target dataset sizes. The subset contains 30% of randomly selected samples from the original dataset. The model performance was tested with different amounts of frozen (i.e. non-trainable) layers. The following configurations were considered: only the top layer is trainable, the first 308 layers are frozen, the first 136 layers are frozen, and all layers are trainable. Table 2 compares the best results achieved on the pre-trained and non-pre-trained models.

Table 2
Comparison of performance of pre-trained and non-pre-trained models on the target datasets

Model	UCI-HAPT		UCI-HAPT subset	
	Accuracy (%)	F1(%)	Accuracy (%)	F1(%)
Not pre-trained DenseNet121	92.23	92.19	86.29	86.38
Pre-trained DenseNet121, only top layer trainable	80.00	77.99	75.60	64.08
Pre-trained DenseNet121, 308 layers frozen	**92.44**	**92.52**	86.90	87.11
Pre-trained DenseNet121, 136 layers frozen	92.23	92.24	**89.11**	**89.27**
Pre-trained DenseNet121, all layers trainable	91.89	91.92	88.31	88.26

As could be seen from Table 2, the use of pre-trained models led to better results both on the whole dataset and on its subset.

Concerning the whole UCI-HAPT dataset, the pre-trained model with 308 frozen layers showed the best results, with an increase of 0.21% for accuracy and 0.33% for the F1-score compared to the non-pre-trained one. However, for other configurations, pre-training resulted in a performance decrease. This fact indicates that the pre-processed UCI-HAPT dataset size is big enough that pre-training may degrade the model's performance, i.e. result in a Negative Transfer.

As for the UCI-HAPT subset, all pre-trained models except one with the only trainable top performed better than the non-pre-trained model. The best results were achieved by the model with 136 frozen layers, increasing accuracy by 2.82% and F1-score by 2.89%. Moreover, as shown in Figure 5, pre-training the models resulted in smoother gradient descent and faster learning.

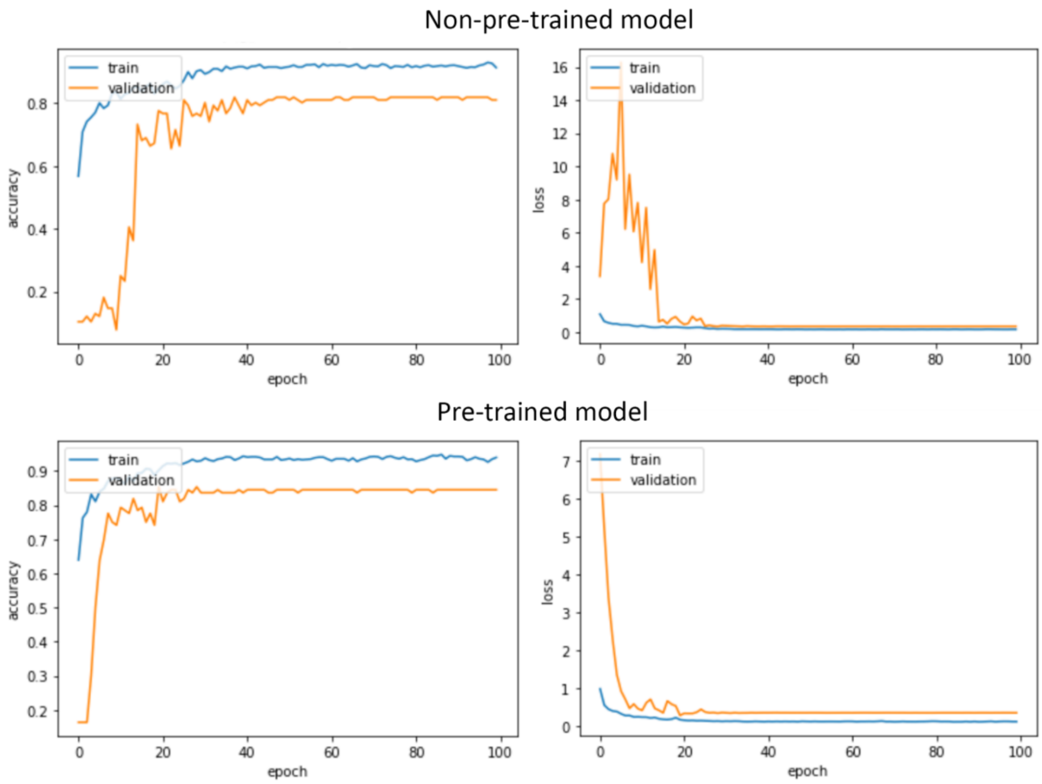

Figure 5: Accuracy and loss values of the non-pre-trained DenseNet121 model and the pre-trained DenseNet121 model with 136 layers frozen during the training on the UCI-HAPT subset.

Summarizing the information obtained, it can be stated that using a pre-trained model, especially with frozen layers, leads to improved performance, smoother gradient descent and faster training on small datasets. However, using a pre-trained model on medium- and large-sized datasets may result in Negative Transfer and degraded performance.

5. Conclusion

In this study, we propose a novel deep-learning model pre-trained on the scalograms generated from the KU-HAR dataset. The nine popular deep-learning architectures and eight CWT configurations were tested, which resulted in 60 possible combinations and 300 models being trained.

It was established that the best results were produced by the model with DenseNet121 architecture, Morlet wavelet and scale value from 0 to 256, which resulted in classification accuracy of 97.48% and F1-score of 97.52% on the KU-HAR dataset, which outperforms most state-of-art works, where this dataset was used.

The proposed pre-trained model was then tested on the pre-processed UCI-HAPT dataset and its subset to determine how the pre-trained model performs on target datasets of different sizes and with some significant distinctions from the source dataset. Usage of the proposed model led to the maximum increase of 0.21% for accuracy and 0.33% for F1-score on the whole UCI-HAPT dataset, and of 2.82% for accuracy and 2.89% for F1-score on the subset, compared to the non-pre-trained models.

It was concluded that using the pre-trained model, especially with frozen layers, leads to improved performance, smoother gradient descent and faster training on small datasets. However, using the proposed model on medium- and large-sized datasets may result in Negative Transfer and degrade the performance.

In the subsequent studies, it is planned to assess more combinations of the neural network architectures and CWT parameters, with further analysis of the influence of the scale values (i.e. scalogram sizes) on models' performance. Moreover, promising is the design and analysis of heterogeneous pre-trained models, for example, with the usage of the Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) layers, as well as developing pre-training models using combined datasets using Inter-Domain Activities Analysis.

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