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DISTRACTED DRIVER BEHAVIOR RECOGNITION USING MODIFIED CAPSULE NETWORKS

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Abstract

Human activity recognition (HAR) is an increasingly active study field within the computer vision community. In HAR, driver behavior can be detected to ensure safe travel. Detect driver behaviors using a capsule network with leave-one-subject-out validation. The study was done using CapsNet with leave-one-subject-out validation to identify driving habits. The proposed method in this study consists of two parts, namely encoder and decoder. The encoder used in this study modifies Sabour's capsule network architecture by adding a convolution layer before going to the primary capsule layer. The proposed method is evaluated using a primary dataset with 10 classes and 300 images for each class. The dataset is split based on hold-out validation and leave-one-subject-out validation. The resulting models were then compared to conventional CNN architecture. The objective of the research is to identify driving behavior. In this study, the proposed method results an accuracy rate of 97.83% in the split dataset using hold-out validation. However, the accuracy decreased by 53.11% when the proposed method was used on a split dataset

using leave-one-subject-out validation. This is because the proposed method extracts all features including the attributes of each participant contained in the input image (user-independent). Thus, the resulting model in this study tends to overfit.

Keywords: capsule network; driver behavior detection; human activity recognition;

I. Introduction

The computer vision community's interest in Human Activity Recognition (HAR) is growing due to the need to construct intelligent systems such as monitoring, control, and analysis [1], [2]. The primary objective of HAR is to determine and predict what humans do based on a set of information [3]. One implementation of HAR is for the recognition of activity during driving.

A vision-based technique can be used to detect driving behavior [4], [5]. The driver's head, torso, upper arms, lower arms, and hands may be captured using a camera mounted on the car's dashboard. The categorization of distracted driving behaviors is typically the focus of the analysis of driving behaviors. This category might alert other drivers to their circumstances, lowering the chance of a collision and ensuring a safe journey [6].

Convolutional Neural Network (CNN) is a deep learning algorithm that is a leading method to address this problem [7]. Example [8] A conventional CNN architecture with three convolutional layers, three pooling layers, and three fully-connected layers was used to classify driving behaviors based on side-view photographs. C. Yan et al. [9] classified driving behaviors based on front-view and side-view pictures with their optical fluxes by combining two stream inputs with interwoven CNN. K. A. AlShalfan et al. [10] classified drivers' behavior based on side-view photos using modified VGG-16. X. Rao [11] driving behaviors are identified based on side view photographs using PCA whitening pre-processing and typical CNN architecture, including four convolutional layers, four pooling layers, and two fully-connected layers.

The majority of studies that have used CNN for driver behavior detection have shown excellent results. However, there might still be a few problems. To begin with, CNN is not equivalent to an affine transformation [12]. Additionally, spatial information in picture data can be removed by downsampling on the pooling layer [13], [14]. However, CNN is not equivariant to affine transformation [15], [16]. By employing capsules rather than neurons and a dynamic routing method to retain the spatial associations between features, a capsule network (CapsNet) can be utilized to address these shortcomings [17], [18], [19]

CapsNet Architecture has been used widely for image classification. CapsNet architecture was able to recognize handwritten Indic characters [20], Devanagari manuscript [21], Car dataset, and Solar Panel dataset [22]. Some studies have also modified CapsNet architecture. F. Kinli et al. [23]

showed that CapsNet was modified by adding three more convolution layers to detect the Fashion dataset. G. Madhu et al. [24] showed that CapsNet was modified by adding four more convolution layers to detect the existence of a malaria parasite in a cell. Fire recognition has become crucial, in area safety using CapsNet [25].

The hold-out validation approach is typically used in image classification to randomly divide the data into training and validation sets. However, for HAR, other sources provided the data. If those training and validation sets were randomly divided, the model might view data from the same subject throughout training and validation [26]. The model's generalizability to new users (user-independent) suffers due to this method. As a result, the split data approach known as leave-one-subject-out is employed.

The objective of the research is to identify driving behavior. The study was done using CapsNet with leave-one-subject-out validation to identify driving habits. This work adds a convolution layer to Sabour's CapsNet architecture to deepen the model before moving on to the top capsule layer. The datasets used to divide by hold-out and leave-one-subject-out validation, the model built from this architecture is expected to deliver great generalization and superior performance than the conventional CNN design.

II. Materials and Method

A. Capsule Network

A capsule serves as the primary low-level node of a type of neural network known as a "CapsNet" [27]. Vectors "length and orientation represent the entities" existence and attributes in the vector activation functions used by CapsNet. CapsNets's utility in resolving challenging computer vision issues has grown with recent developments in their routing methods [28]. CapsNet stores data at a vector level instead of convolutional neural networks[29].

The amplitude and direction of the vector neuron in CapsNet are identical to those of an average vector [30]. The length of the vector neuron represents the probability of an object being present at a particular position in the image. Meanwhile, the orientation represents the image's attitude.

A capsule in the layer contains an activity vector used to estimate the instantiation parameters of the secondary capsule at the layer using the trainable weight matrix, as shown in (1). The prediction vector shows the contribution made by the first capsule to the secondary capsule. In CapsNet, a dynamic routing algorithm maintains spatial relationships between features. Dynamic routing between capsules was first developed by Sara Sabour. It is used to train the CapsNet iteratively. Each primary capsule in the bottom layer l delivers all capsules in the subsequent layer $l+1$. The matrix transformation will then anticipate the secondary capsule's instantiation parameters. The result of the matrix transformation represents the agreement with the secondary capsule. If the multiple predictions agree, then the two capsules are relevant to each other, and it will activate the secondary capsule [31].

A capsule i in the layer l contains an activity vector u_i that is used to estimate the instantiation parameters $\hat{u}_{j|i}$ of the subsequent capsule j at layer $l+1$ applying the trainable weight matrix w_{ij}, as shown in (1). The prediction vector $\hat{u}_{j|i}$ reflects how much the central capsule i assists the subsequent capsule j.

$$\hat{u}_{i|j} = w_{ij} u_j \tag{1}$$

A coupling parameter c_{ij} connected with the prediction vector indicates the agreement between both capsules. The coupling coefficient c_{ij} of capsule i is determined by routing softmax, which can be seen in (2), representing b_{ij} the log prior probability that the capsule i is associated with the capsule j.

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})} \tag{2}$$

Equation (3) calculates a weighted total of s_j of all these main capsule predictions, which is the output of the secondary capsule.

$$s_j = \sum_i x_{ij} \cdot \hat{u}_{j|i} \tag{3}$$

The resultant output is then squashed using the activation function v_j to make sure that the length of the capsule result is between 0 and 1. Equation (4) depicts the squashing activation function.

$$v_j = \frac{\|s_j\|^2}{1+\|s_j\|^2} \cdot \frac{s_j}{\|s_j\|} \tag{4}$$

As shown in (5), the agreement between the expected and actual outputs is computed by calculating their dot product. The capsules create an exact spatial connection if the resultant dot product is a large scalar.

$$a_{ij} = v_j \cdot \hat{u}_{j|i} \tag{5}$$

B. Margin Loss

Margin loss is mathematically defined as in (6).

$$L_k = T_k \max(0, m^+ - \|v_k\|)^2 + \lambda(1 - T_k)\max(0, \|v_k\| - m^-)^2 \tag{6}$$

where $T_k = 1$ for the correct prediction and $T_k = 0$ otherwise. The higher $m^+ = 0.9$ and the lower $m^- = 0.1$ thresholds for the correct and wrong classes, respectively. Meanwhile, $\lambda = 0.5$ is employed for numerical stability.

C. The Architecture

An auto-encoder is embedded into the architecture. A decoder and an encoder are two essential elements. The encoder structure, as seen in Figure 1, is the initial component. It includes four layers, including a fully linked digit capsule layer and three convolutional layers. Following the ReLU activation function, the first convolutional layer consists of 128 kernels, each measuring 10×10 units, and it operates with a stride of 2. The ReLU activation function is followed by the second convolution layer, which has 256 8×8 kernels with a stride of 2. In 2D pictures, the first two convolutional layers identify fundamental characteristics.

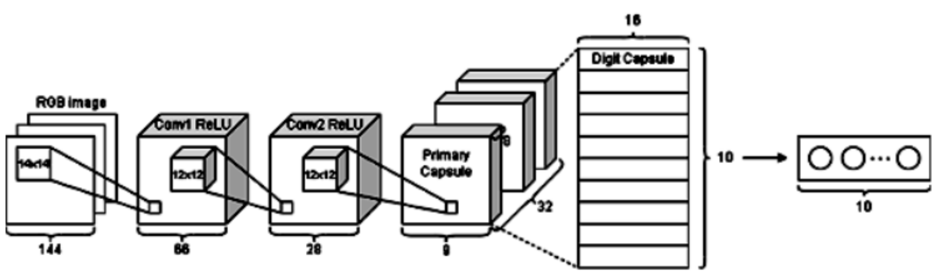


Figure 1. The Encoder Architectures

The third layer is a convolutional capsule layer representing the primary capsule layer. It contains 8D convolutional capsules with 32 channels. Each essential capsule employs eight convolutional units with a kernel of 8×8and a stride of two. The main capsule has an 8D vector with 6×6×32 capsule outputs. The last layer is the digit capsule layer. It has one 16D capsule for each digit class, and each is fully linked to all the capsules in the preceding layer. A dynamic routing mechanism is used between the main and digit capsule layers.

The second part is the decoder structure, shown in Figure 2. The decoder structure recreates a picture from the output of the proper digit capsule by delivering it into three fully connected layers. These layers learn to recreate a 96×96 RGB image by keeping essential features. The loss function is calculated during training by minimizing the Euclidean distance between the reconstructed and input images. The overall CapsNet architecture in detail can be seen in Table 1.

HAR refers to the motion of one or more human bodily parts [32]. HAR aims to automatically interpret human body gesture or motion and determine what human does through a collection of observations [33]. HAR should designate the same action with the same name even if it is performed by different persons in various settings or environments [34]. In this study, two conditions are used for both implementation and evaluation.

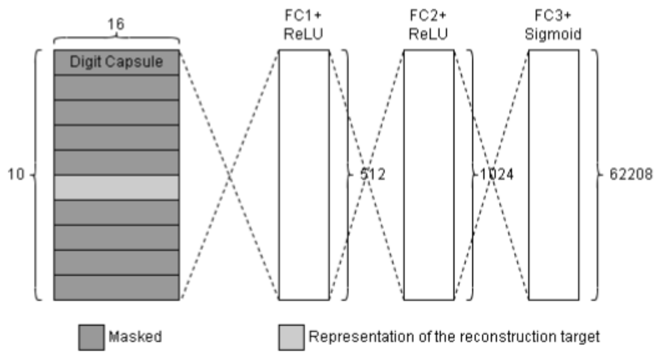


Figure 2. The Decoder Architectures

Table 1.

The architecture of the proposed method in detail

Layer	**Output Shape**	**Unit**
Input Image	144, 144, 3	0
Convolutional #1	66, 66, 128	75,392
Convolutional #2	28, 28, 256	4,718,848
Primary Capsule	9, 9, 32, 8	9,437,440
Digit Capsule	16, 10	3,369,600
Fully Connected #1	512	82,432
Fully Connected #2	1024	525,312
Fully Connected #3	62208	63,763,200
Total Trainable Params		81,972,224

The first employs hold-out validation, based on dividing the dataset into two subsets: training and validation sets. 80% of a dataset is used for training and 20% for validation. It is less costly to compute because it only has to be performed once, but the model's conclusions may alter if the data is divided again. Hold-out validation indicates that accuracy depends on the subject chosen for evaluation [35].

The second one uses the leave-one-subject-out validation. Leave-one-subject-out validation is a variant of hold-out validation, where one subject is considered for the validation and others for training the model [36]. This approach makes the model evaluate new subjects. Here, we want to observe the model's capability for user independence conditions.

D. Experimental Setup

This study collected 3000 images from four participants performing ten activities in the car. The data from those participants are collected using a Logitech camera placed on the left side of the dashboard. Each participant is asked to perform ten different activities and then recorded. The behavior reflect one safe driving behavior that leads to safe travel and nine behavior that lead to hazardous travel. Each behavior becomes a classification class in this study, as shown in Table 2, whereas the data samples are shown in Figure 3. The camera position is placed parallel to the subject which can display all the classes described in Table 2 that were tested.

Table 2.
Dataset description

Class	**Description**[a]
C0	Safe driving
C1	Texting with right hand
C2	Talking on phone with right hand
C3	Texting with left hand
C4	Talking on phone with left hand
C5	Adjusting radio
C6	Drinking
C7	Reaching behind
C8	Doing hair and makeup

[a]*Source*: www.kaggle.com

Assess user-dependent and user-independent models by modelling and evaluating image data through hold-out and leave-one-subject-out validation techniques. In the first approach, the dataset is partitioned into two subsets: the training and validation sets, with a random split of 80% for training and 20% for validation. Conversely, three subjects are utilized for the training set in the leave-one-subject-out validation, while one is reserved for the validation set.

The data were rescaled into 144×144 pixels for pre-processing, and RGB features were extracted as input and normalized by dividing each pixel in the image by 255 so that each pixel in the data ranges from 0 to 1. Normalizing is done to simplify further calculations.

Google Collab with a standard GPU is used to compile the model. The data is trained with the Adam optimizer and a learning rate of 0.0001. In this research, 100 epochs with a batch size of 60 were utilized to evaluate the proposed method's performance in hold-out validation, and a batch size of 75 was used to evaluate the proposed method's performance in leave-one-subject-out validation.

Figure 3. The samples of the data

The suggested method's performance on the model is then assessed using an accuracy measure and a loss function generated from the total margin and reconstruction losses. The model's performance is then compared to a popular CNN design, which contains three convolutional layers, a pooling layer, and three fully linked layers at the end. The kernel and configuration used in this architecture are the same as those used in CapsNet architecture.

Every subject in the picture has unique information; the convolutionally (CNN) model evaluates each image, regardless of whether the same individual has long or short hair, wearing a headscarf/hijab or not, and so forth. CapsNet is used in conjunction with user-dependent and user-independent models in this study. The hypothesis posits that dependent users, regardless of whether they wear the hijab or not, will yield good accuracy since all subjects are included in the testing population, while independent users will create poor accuracy due to the existence of subjects outside the testing population.

III. Result and Discussion

A. Performance of the Proposed Method Based on Hold-out Validation

Figures 4 and 5 show the accuracy and loss of the suggested technique. The figures show that the suggested approach becomes convergent after the 60th epoch. Furthermore, the difference between the training and validation sets is slight in the 100th epoch. These minor variations demonstrate that the suggested strategy works effectively when all individuals are included in the training and validation sets.

Table 3 shows the suggested method's confusion matrix. The proposed method can properly and efficiently recognize image data in the behavior of "drinking," "C6," and "reaching behind" "C7". The proposed method may readily distinguish picture data in the behavior of "talking on the phone with the right hand" "C2" and "talking to a passenger" "C9". However, they also retrieve some image data from other behaviors that are not relevant to these behaviors. On the other hand, the proposed method can retrieve all the relevant image data in the behavior of "texting with the right hand" "C1", but there is an instance from this behavior that is misclassified to the other behavior. These errors occur due to the similarity of features with other behaviors. This similarity results in low inter-class variability and leads to misclassification.

Table 3.

Confusion matrix of the proposed method based on hold-out validation

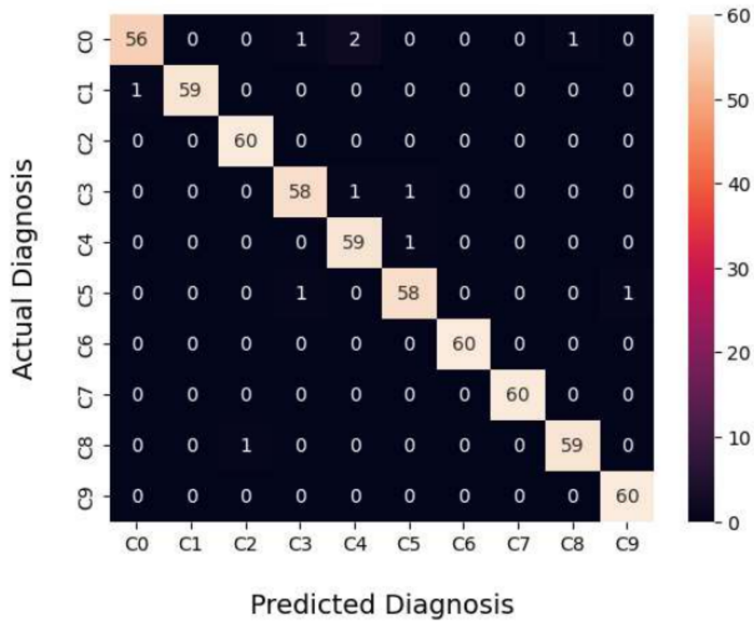


Figure 4. The proposed method's training and validation accuracy are based on hold-out validation

Figure 5. Training and validation loss of the proposed method based on hold-out validation

The proposed method incorporates the reconstruction loss, which calculates the disparity between the input and reconstructed images. The reconstructed images are utilized as regularization to prevent overfitting. Figure 6 shows examples of the reconstructed picture data used in this research.

The proposed method is compared to the popular CNN design, as shown in Table 4. It is used to assess the effectiveness of the suggested approach based on hold-out validation. The loss performance of the popular CNN architecture is roughly 3.58 times greater than the proposed approach. This difference demonstrates that the suggested technique is more likely to predict a value than the current CNN method. As a result, the proposed method works better than the conventional CNN architecture when applied to hold-out validation.

Figure 6. Reconstructed image of the proposed method based on hold-out validation

Table 4.

Performance comparison of the proposed technique with popular CNN architecture based on hold-out validation

Architecture	Training Set		Validation Set	
	Accuracy	**Loss**	**Accuracy**	**Loss**
Proposed Method	100%	0.0034	98.17%	0.0262
Conventional CNN	100%	2.5e-4	97.83%	0.0938

B. Performance of the Proposed Method Based on Leave-one-subject-out Validation

The accuracy and loss of the proposed method can be seen respectively in Figure 7 and Figure 8. From those figures, the gap between the training and validation sets is quite prominent in the 100th epoch. This prominent gap shows that the proposed method has not worked well when a new participant is used in the validation set. Nonetheless, the proposed method is still trying to study the features of new participants. It can be seen from the loss graph, which is still decreasing overall. As a result, the proposed approach may recognize the driver behavior of a new participant.

Table 5 shows the proposed method's confusion matrix. The proposed method can recognize image data in the behavior of "reaching behind" "C7" quite well. However, it retrieves some image data from other behaviors that are not relevant to these behaviors.

Figure 7. Training and validation accuracy of the proposed method based on leave-one-subject-out validation

However, the proposed method can retrieve the most relevant image data in "talking on the phone with the right hand" and "C2". However, some image data from this behavior is misclassified to the other behavior. These errors occur because a new user (user-independent) is used as an input, which results in a change in intra-class variability so that the proposed method experiences a decrease in performance.

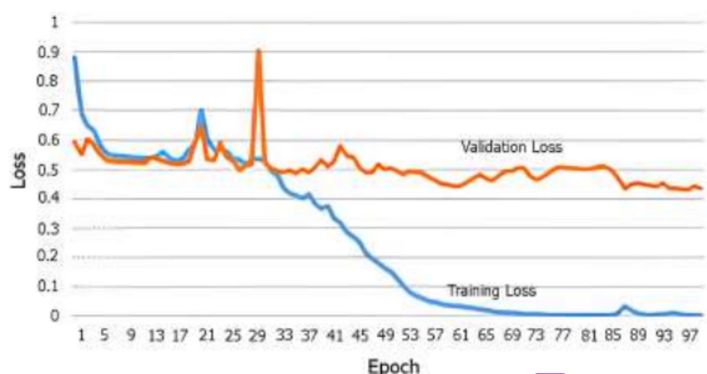
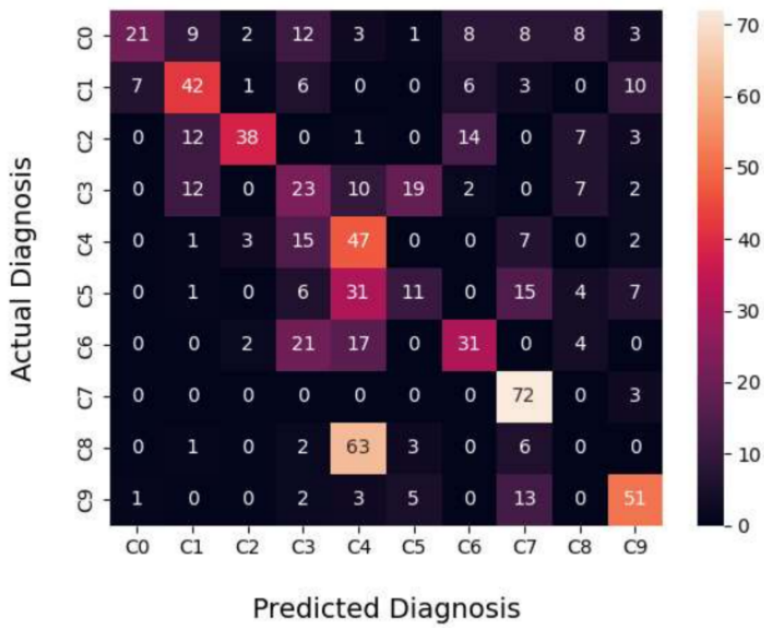


Figure 8. Training and validation loss of the proposed method based on leave-one-subject-out validation

Table 5.

Confusion matrix of the proposed approach based on leave-one-subject-out validation



The samples of the reconstructed image data in this study can be seen in Figure 9. From that figure, the reconstructed images show that the proposed method has generalized the user. However, the proposed method still extracts unnecessary features and instead loses essential features that make the proposed method unable to distinguish one driver's behavior from another.

The proposed method is then compared to the conventional CNN architecture that can be seen in Table 6. It is used to examine the efficacy of the proposed method employing leave-one-subject-out validation. According to the table, the proposed method outperforms the popular CNN design.

Figure 9. Reconstructed image of the proposed method based on leave-one-subject-out validation

However, the proposed method's effectiveness could be improved in the validation set. In the training set, the proposed approach detects driving behavior effectively. However, it is less able to detect the driver behavior in the validation set due to new participants used in the validation set.

In this case, the auto-encoder, as a dimensionality reduction, can still not generate a model with a good generalization.

Table 6.
Performance comparison of the proposed method with conventional CNN architecture according to validation with one subject left out

Architecture	**Training Set**		**Validation Set**	
	Accuracy	**Loss**	**Accuracy**	**Loss**
Proposed Method	100.00%	0.0058	44.80%	0.4310
Conventional CNN	100.00%	4.3e-6	36.93 %	8.2506

IV. Conclusion

In this study, modified Sabour's CapsNet is used to identify the driver behavior. The dataset is modeled using CapsNet architecture. It is then evaluated by using hold-out validation and leave-one-subject-out validation. It is also compared to the conventional CNN architecture to evaluate the effectiveness of the proposed method. The proposed method can provide better performance compared to the conventional CNN when it is applied to hold-out validation because it uses an auto-encoder to avoid overfitting problems. However, the proposed method experienced a decrease in performance by 54.36% when the new user (user-independent) was used as an input to identify the driver's behavior. This shows that the regularization used in the proposed method is still not robust to user variability. That makes the resulting model still prone to overfitting. Therefore, further study can be performed with better regularization so the resulting performance will remain stable under various circumstances or environments.

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