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A Residual Network with Focal Loss to Handle Class-imbalance Problem on Nurse Care Activity Recognition

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***Abstract*—Human Activity Recognition (HAR) is a remarkable basement for the development of the generalized and robust machine learning modeling, as this domain typically has to deal with high-dimensional sensor data that are characterized by a large mutability (e.g., due to the diversity of the user's actions or as the aggregate of noise). However, unlike other domains, HAR is a very challenging task because of the large scale of class-imbalance, lack of a good benchmark dataset for HAR, and different experimental setups (e.g., several types of sensors or changes in their locations). Highly imbalanced data forces the model to show large bias towards the majority class and thus, minority classes are almost ignored. On the "The 2nd Nurse Care Activity Recognition Challenge Using Lab and Field Data" dataset, we present a deep learning paradigm that is compiled with multi-class focus loss and residual block network. In our proposed model, the residual block network prevents the model from vanishing gradient problems in a deep learning network and focal loss overcomes the crucial class-imbalance problem. On the test data, we achieved a promising accuracy of 34.47%, beating the previous state-of-the-art algorithms.**

***Contribution*—Using cost-sensitive learning (focal loss) and the fusion technique, our proposed methodology ensures a better classification of complex nurses' activities, thereby resolving the constraint of class-imbalance.**

***Index Terms*—nurse care, activity recognition, class-imbalance, focal loss, residual network**

I. Introduction

HAR is a vast topic of case study that focuses on detecting a person's work or behavior based on sensor data. This field has enormous applications because of its social context with computer systems and its characteristics such as availability of the sensors, portable, simple environmental setups, low cost, and easy to handle than other domains (e.g., video or image data). That is why many kinds of research were performed based on wearable sensors. In consequence, HAR is apt to smart home, security and surveillance applications, healthcare and elderly care monitoring solutions, behavior and pattern analysis, and so forth.

However, activity recognition in nurse care is requisite for conducting reliable care services in care centers such as smart care hospitals or homes. It helps to improve the overall nurse care facilities for instance measuring the performance of the nurses, improvement of the nurse training, identification of abnormal activities, compliance of the given routine, and so on. After all, these approaches reduce hospitalization time and cost. But there are a lot more difficulties to execute HAR using sensor data. For instance, nurses have to perform several activities not only themselves but also the patients which create a wide range of diversity among the same class. In addition, one activity can be the composition of several sub-activity resulting in the recognition task being more challenging. Besides, recognition tasks may be more difficult due to the changes in the sensors or their locations, failure of the sensors, noisy data, non-uniform sampling rate while collecting the data, and so on.

Here, we have introduced a robust deep residual network that can correctly classify highly imbalanced complex nurse care activities. The primary goal of our work is to automate the healthcare system and improve the overall care services.

The main contributions of our model are illustrated below:

- Exploring focal loss to effectively handle the class-imbalance problem.
- Developing of neural network using residual block to solve vanishing gradient problem in the neural network.
- Employing a fusion technique for better classification from multiple models.

In this paper, related works and datasets are discussed in Section II as well as Section III, respectively. Class-imbalance and vanishing gradient problems can be solved using the focal loss function and residual network demonstrates in Section IV. Finally, in Section V, we wrap up the article with a few recommendations for the future.

II. RELATED WORKS

HAR using sensor data is an exploring research area due to the availability of the wearable mobile sensor, embedding of the accelerometer sensor into smartphones, low cost and power consumption, and simple environmental setup [2], [3], [6]. There have been a lot of remarkable papers on HAR, but just a handful on nursing care activity recognition. A lot of machine learning and deep learning methodologies have been

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addressed by many researchers in activity recognition.

The "Nurse Care Activity Recognition Challenge" [1], [7] was held in 2019 and 2020, and different participant teams performed quite well on these datasets using both classic and deep learning models. The authors of [8] employed an ensemble of K-Nearest Neighbors (KNN) classifiers on multiple hand-crafted features derived from raw data in the 2019 competition, including raw data obtained via motion capture, Meditag, and accelerometer sensors. For that competition, another recognition pipeline based on the Spatial-Temporal Graph Convolutional Network (ST-GCN) to recognize activities from 3D motion capture data was submitted by [9]. A two-layers stacked Gated Recurrent Unit (GRU) module with a simple and context attention mechanism was proposed by [10] for nurse activity recognition. They compiled four different models and finally combined them for class-wise score and the person-wise one leave out cross-validation methodology yielded a 66.43% accuracy.

In the 2020 competition, the authors of [11] used features engineering-based classical machine learning approach for classification tasks using Random Forest (RF) Classifier and obtained a promising accuracy of 65% using stratified 10-fold cross-validation technique. Another algorithmic pipeline was proposed by [12] consisting of re-sampling, features selection based on Gini impurity, and validation with Stratified K-Fold cross-validation using RF classifier and achieved 65.9% of cross-validation accuracy.

Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been shown in recent research to be effective at detecting human dynamic behaviors. Combining CNN and RNN can lead to high recognition precision, and Inoue et al. suggested one such architecture [13]. Because of the capacity of analyzing patterns of human behavior, Zia Uddin at. el. [14] developed such CNN architecture. After Z-score normalization, they retrieved Gaussian kernel-based PCA features from raw data and fed them to the network. The author of [15] presented a new CNN architecture for multi-channel time series that can both extract features and classify them. Throughout the model, they attempted to decipher the hidden pattern of human action.

Deep learning models perform outstandingly over classical machine learning models. Because the obtained sensor data is analyzed and distilled using traditional machine learning algorithms from the field of signal processing. Due to the domain or sensor-specific, classical machine learning models may not be a good choice for generalizing HAR tasks. Besides, domain expertise requires analyzing the raw data and feature engineering to fit the model. On the contrary, the capability of automatic feature extraction from the raw data, the deep learning model is more preferable for generalizing AR tasks. Most of the researchers in this domain address a major challenge while handling the data is a large-scale class-imbalance. For the classical machine learning methodology, up-sampling of the minority class and down-sampling of the majority class is a decision of interest to resolve the problem of class-imbalance. But in the deep learning framework, it is quite difficult to handle this problem. In this paper, we propose a deep learning-based model to address these issues to recognize the complex nurse care activities on "The 2nd Nurse Care Activity Recognition Challenge Using Lab and Field Data" dataset.

III. Dataset Description

The dataset belongs to the activities of the nurses in the nurse caring center of elderly people. The detailed dataset description and the data capturing the environment of the dataset are provided in this section.

A. Data Capturing Environment

The data is recorded from two environmental setups. The first is **Lab data** collected at the Kyushu Institute of Technology's Smart Life Care Unit [16]. Seven professional nurses participated in collecting the data and data is captured by the accelerometer sensor embedded into the smartphone and motion capture sensor [17]. The nurses' right arm had an accelerometer sensor implanted in it. They had to perform the listed activities with 5 repetitions of each activity. Data were collected for 3 days and there was no training phase.

The second step of data collection was performed at a Care Facility in Japan titled after **Field data**. There were 42 nurses collecting data in this setup. Smart phone's accelerometer sensor was used for collecting data. The nurses were not given any instructions other than to use the smartphone application to capture data for particular activities. Data were continuously recorded during the activities. There were 14 days of training phase before recording the actual data and 31 days for collecting the actual data.

B. Challenges of Dataset

The dataset [1] contains total 12 classes those are categorized into 3 major types (Help in Mobility, Assistance in Transfer, Position Change) shown in Figure 1.

Major Activity Name	Activity Label	Label (Dataset)	Activity Name
Help in mobility	A1	1	Guide (from the front)
	A2	2	Partial assistance
	A3	3	Walker
	A4	4	Wheelchair
Assistance in Transfer	B1	5	All assistance
	B2	6	Partial assistance (from the front)
	B3	7	Partial assistance (from the side)
	B4	8	Partial assistance (from the back)
Position change	C1	9	To Supine position
	C2	9	To Right Lying position
	C3	10	To Left Lying position
	C4	11	Lower body lifting
	C5	12	Horizontal movement

Fig. 1. List of activities performed by nurses

There are two different activities (C1 and C2) labeled as activity 9 in the dataset description that is considered to be identical. Six users' data from the field and two users' data from the lab were opened for training, while three users' data from the field was opened for testing. The data were continuously collected from the accelerometer sensor at a sampling rate of 60 Hz. No reprocessing method is applied to the dataset. There were many unlabeled data both from field data and lab data. There were about 2.1% to 4.4% missing data for the training users and about 2.1% to 7.3% for the test users. The duration of activities of the training dataset is shown in Figure 2. The main challenge of the dataset is a high class-imbalance of the train and test data. There was a large scale of class-imbalance among both train and test data, as shown in Figures 3, 4, and 5. About 50 million data units were there in the training data and about 40 million data units in test data. The challenge is to predict the activity label of the test data using a generalized model using field and lab data [11].

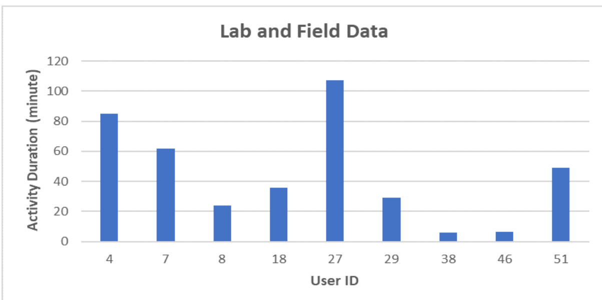

Fig. 2. Duration of the total activities performed by each Field and Lab user

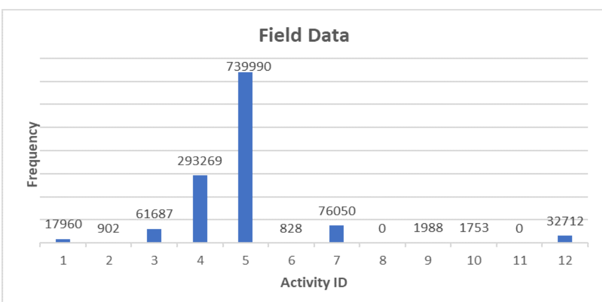

Fig. 3. Field data histogram plot

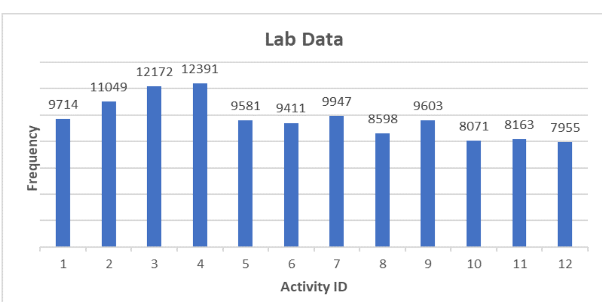

Fig. 4. Lab data histogram plot

IV. Methodology

In this section, we represent our full procedure for recognizing 12 different nurse care activities. We used a deep neural network (with residual block) with multi-class focal loss to

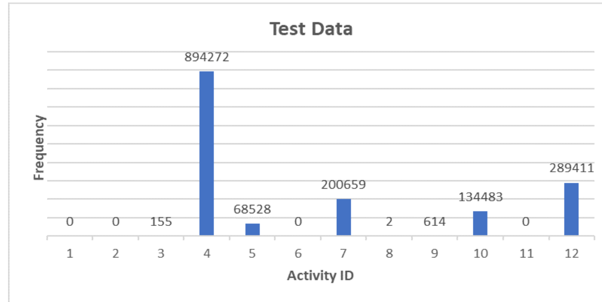

Fig. 5. Test data histogram plot

classify these activities. Our proposed method consists of 3 major steps: Data Preprocessing, Focal Loss design, and finally model training with multi-class focal loss.

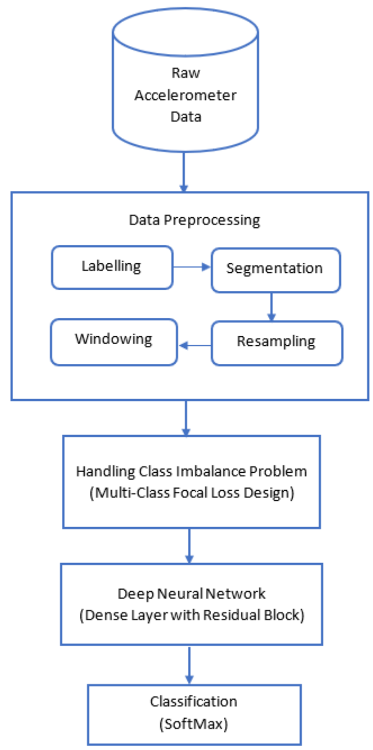

Fig. 6. Block diagram of our proposed method

A. Data Preprocessing

The provided training dataset consists of Lab data folder and a Field data folder. Each folder contains accelerometer sensor data (x, y, z) with different timestamps and labels files. The label file contains an activity label with starting timestamp and finish timestamp of a particular activity. At first, both accelerometer data and label files were sorted by date and time. Then, we merged both label files and accelerometer data into a single data frame for model training. We found that there were many accelerometer data for whom labels were not provided and so, we dropped those data. The dataset was not properly sampled and there were many missing accelerometer data. To mitigate these problems, we re-sampled the dataset to a fixed sampling frequency 20Hz frequency for different activity labels. Finally, the sensor signals (accelerometer) were preprocessed by sampling in fixed-width sliding windows of 10 sec and 90% overlapping (200 readings/window). The workflow of our proposed method is shown in Figure 6.

B. Focal Loss

Tsung-Yi et al. [19] applied focal loss for dense object detection in the imbalance dataset. They modified the standard cross-entropy (CE) loss which down-weights the loss assigned to well-classified examples to solve the foreground-background class-imbalance problem [19]. Focal Loss (FL) is an upgraded version of CE Loss that attempts to reduce the class-imbalance problem by allocating more weights to hardly classified and confusing examples. When the model can correctly classify an example easily, the loss is reduced by using the focal loss function. This method solves the issue of class-imbalance by directing the loss's attention to hard classes. To explain focal loss in short, standard binary Cross-Entropy [20] loss function for classification defined mathematically is given below:

$$CE_{(p,\gamma)} = \begin{cases} -\log(p) & \text{if } \gamma = 1 \\ -\log(1-p) & \text{otherwise} \end{cases} \tag{1}$$

Here $p \in [0,1]$ refers to the model's predicted probability if ground truth value of the sample is 1 and $\gamma \in \{\pm 1\}$ denotes to the ground truth class. For multi-class classification, we calculate p_t as follows:

$$p_t = \begin{cases} p & \text{if } \gamma = 1 \\ 1-p & \text{otherwise} \end{cases} \tag{2}$$

CE loss establishes an upper constraint on the KL-divergence between the target and predicted distribution by minimizing the KL loss [23]. From equation (2), the CE function can be presented as follows:

$$CE_{(p,\gamma)} = CE_{(p_t)} = -\log_{(p_t)} \tag{3}$$

One remarkable characteristic of this loss is that even easily classified samples ($p_t >> 0.5$) suffers a loss of non-trivial magnitude. But the sum of the loss over a large number of well classified sampled results in a significant impact on the rare classes [19]. To reduce this class-imbalance issue, finally, we can use a weighting factor α for one class and $(1-\alpha)$ for the other class. Here α may be set by the inverse class frequency of the samples or as a hyper-parameter to set by cross-validation data.

$$CE_{(p,\gamma)} = -\alpha_t \log_{(p_t)} \tag{4}$$

This loss function is regarded as a simple extension of CE which is the basis of focal loss. Focal Loss L_f is an extended version of cross-entropy loss with including an extra significant term given in equation (5).

$$L_f = \alpha_t (1-p_t)^{\beta} \log{(p_t)} \tag{5}$$

where α and β are two adaptable parameters. A generic version of focal loss may be demonstrated to represent an upper constraint on the regularized KL-divergence, where the regularizer is the negative entropy of the predicted distribution, and the regularization parameter β is the hyper-parameter of the focal loss [23].

$$\alpha_t = \begin{cases} \alpha & \text{if } \gamma = 1 \\ 1-\alpha & \text{otherwise} \end{cases} \tag{6}$$

Here, the parameter β denotes a predefined positive value that regulates the rate at which the examples are to be down-weighted for a specific class. If $\beta = 0$, the focal loss L_f transforms into categorical CE loss. By increasing the value of β, result in the efficiency of modulating factor increase too ($\beta = 2$ is an optimal value for several experiments). Moreover, α is used as a predefined parameter between 0 and 1 can be set as follow:

$$\alpha_t = \frac{\frac{1}{f_t}}{\sum_{t=1}^{n} \frac{1}{f_t}} \tag{7}$$

where f_t denotes the frequency of a particular class t and n is the total number of classes.

C. Architecture of the Proposed Model

Our classification model is based on a deep neural network is shown in Figure 7. The proposed model is composed of several residual blocks along with fully connected layers. Each residual block consists of some skip connection to the previous layers with the ReLU activation function. Residual block prevents the gradient of the network from being diminished. To prevent over-fitting, we have randomly dropped out the network connection at a fixed rate. Batch Normalization is also used for speeding up the training process. The operation of each fully connected layer follows the equation (8):

$$a^{[l]} = g(W^{[l]} a^{[l-1]} + b^{[l]}) \tag{8}$$

where, $W^{[l]}$ and $b^{[l]}$ signify the weight and bias of a certain layer l and g denotes an activation function (e.g., ReLU).

1) Residual Block and SoftMax Layer: A residual block is a stack of layers organized in such a manner that the output of one layer adds another layer deeper into the network [21]. This bypass link is known as a skip connection, and it prevents the network's gradient from vanishing. The following formula can be used to calculate a residual block with a skip connection from layer l to $(l+2)$:

$$a^{[l+2]} = g(Z^{[l+2]} + a^{[l]}) \tag{9}$$

where,

$$Z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]} \tag{10}$$

Hence, equation (9) becomes,

$$a^{[l+2]} = g(W^{[l+2]} a^{[l+1]} + b^{[l+2]} + a^{[l]}) \tag{11}$$

A SoftMax layer is used to obtain the probability distribution of a particular class often used as the last layer of the model

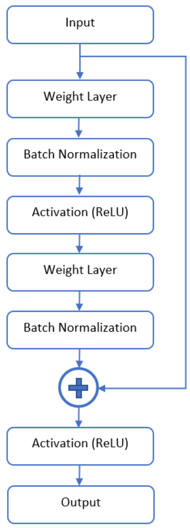

Fig. 7. Block diagram of Residual Block

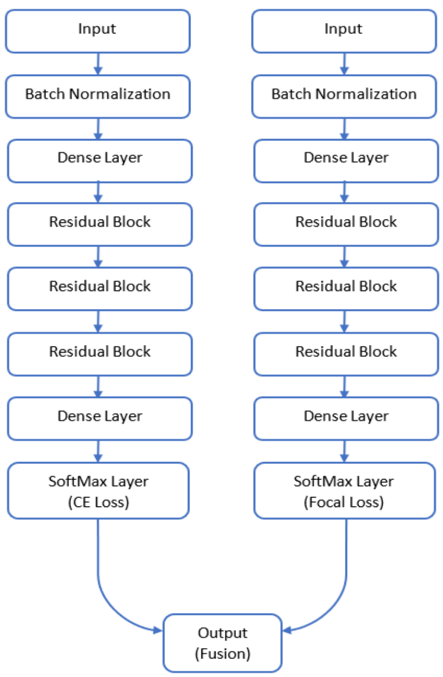

Fig. 8. Block diagram of our proposed model (fusion)

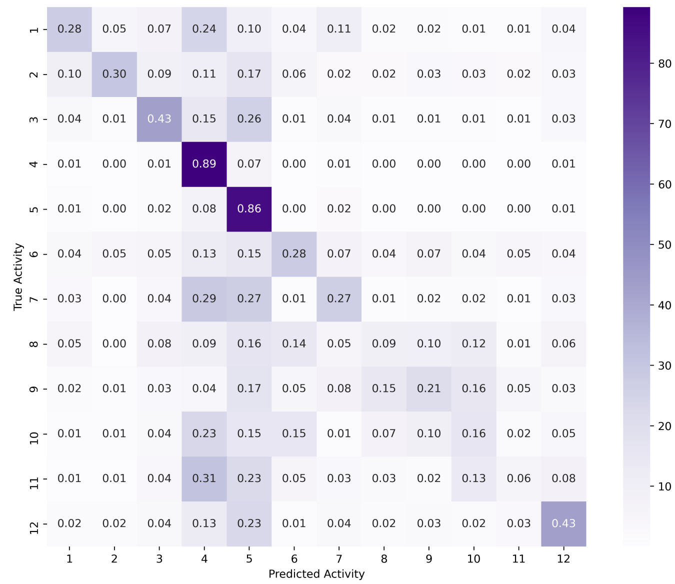

Fig. 9. Confusion matrix obtained using cross-entropy loss on validation data.

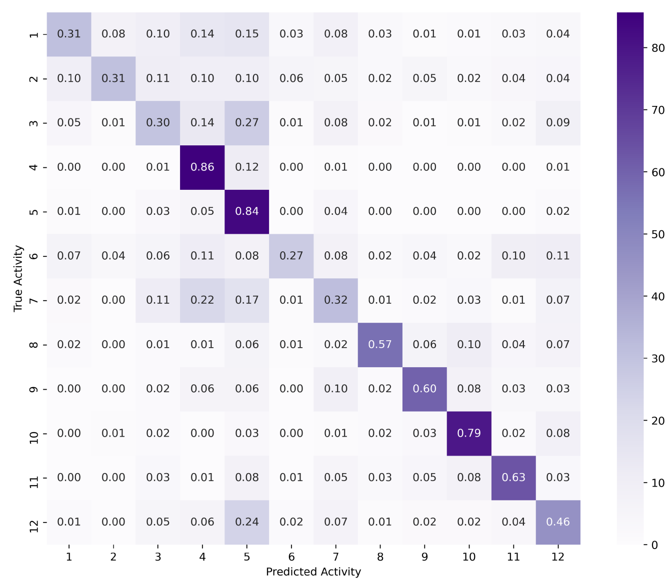

Fig. 10. Confusion matrix obtained using focal loss on validation data.

for classification task [22]. Typically, this layer calculates the classification score using the following equation:

$$output = \underset{t}{\operatorname{argmax}} \frac{e^{a_{(t)}^{[l]}}}{\sum_t e^{a_{(t)}^{[l]}}} \tag{12}$$

where $a_{(t)}^{[l]}$ is the activation of the last layer of a particular class t.

2) Combining the Models' Outputs: Fusion mechanism is a technique where several pre-trained models' outputs are merged to get better classification performance. There are many techniques for compiling fusion mechanisms. One of them is the hand-crafted fusion where the weight of a particular model is set manually. But in this problem, our model has learned to figure out the weight for the final classification. We have used the late fusion technique in our model. The normalized weights are trained after training the two models separately. One model is compiled with traditional cross-entropy loss and another one using multi-class focal loss. While training the fusion model, the other two models' parameters are set to be non-trainable. After training the fusion model, we have obtained the final output using the weights learned by the fusion model. The parameters of the focal loss model and weights obtained by the fusion model are shown

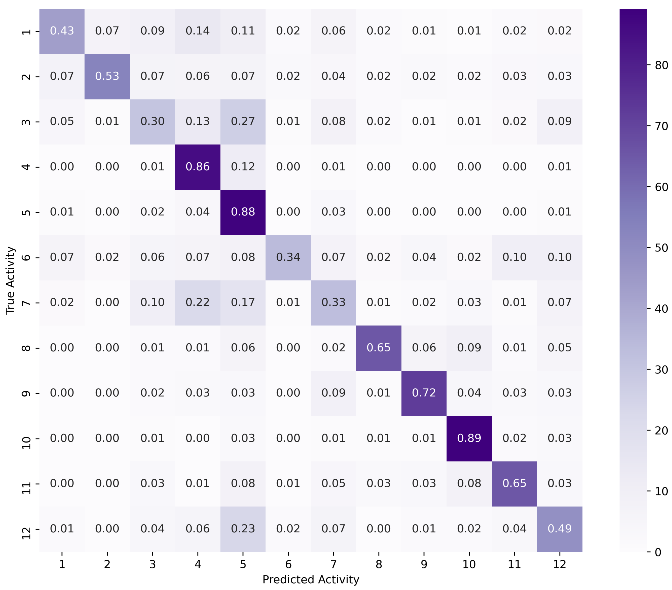

Fig. 11. Confusion matrix obtained using fusion model on validation data

in TABLE III. The fusion mechanism boosts the overall classification performance, as discussed in the following Section.

V. Result and Analysis

For complex nurse care activity recognition, we have trained 3 different modes: deep neural network with categorical cross-entropy loss, a deep neural network with multi-class focal loss, and fusion of these two models. The primary objective to choose this type of architecture is the performance score on the minority classes. The performance score of several minor classes is very poor show in the confusion matrix of Figure 9. Firstly, we have trained the two models separately and then the fusion model is trained by setting these models' parameters (CE loss and focal loss) not to be trained. The fusion model performs better than the other two models shown in TABLE II. We used overall 85% data for the training set and 15% data for the validation set. Validation data is randomly selected from the total lab and field data. Validation split is performed before windowing because after performing windowing there are about 90% overlapping between two windows which can create the validation set similar to the training set. We have used Adaptive Momentum (Adam) as the optimizer for our model which has a 0.001 learning rate. The dropout rate of the neuron is 20%. We have trained the model over 70 epochs. The overall classification score of our proposed models is shown in TABLE I. The score is predicated on the test data of the competition. The table shows that the combining of two models improves the ability to recognize complex nurse care activities. Confusion matrix of three different model is shown in Figures 9, 10, and 11.

From the confusion matrices, it is noteworthy that the traditional deep learning model with categorical cross-entropy loss performs well on majority sampled classes but very poorly on minority sampled classes. On the contrary, the deep learning model with multi-class focal loss generalizes the prediction on both major and minor classes. But there is a small penalty of misclassifying the major class due to the low attendance on the major class. This model inherits from two base models where one can well classify on majority major class and another on minor class. By using the fusion model, the accuracy of both major and minor classes are improved shown in the confusion metrics. The main reason for improving the overall accuracy is the fusion weights set by the fusion model shown in TABLE III. It assigns more weights based on the class-wise accuracy among the two models. Majority classes are set more priority for CE loss model and minority classes for focal loss model.

TABLE I
Performance comparison of our proposed three models on validation data

Model	Accuracy (%)	F1-score (%)	ROC_AUC (%)
DNN with CE Loss	72.12	31.43	44.35
DNN with Focal Loss	74.35	46.41	49.44
Fusion of Two Models*	77.57	50.66	53.97

TABLE II
Performance comparison of our model with existing work on test data

Team	Model	Accuracy (%)
Healthy Vibes	Deep-LSTM	0.17
DataDrivers_BD	CNN	0.76
Gudetama	RFC	1.25
Hex Code	RFC	10.58
UCCLab	RFC	12.26
Britter Baire	RFC	15.53
Team Appophis	RFC	19.39
MoonShot_BD	KNN	22.35
Our Proposed Models	DNN with CE Loss	27.4
	DNN with Focal Loss	32.51
	Fusion of Two Models*	34.47

We have shown the classification accuracy of our model with existing models on the test dataset shown in TABLE II. {We have implemented a robust architecture for recognizing the nurses' care activities. The principle goal of this type of architecture is to solve the class-imbalance problem using focal loss for minority classes. On the other hand, the penalty (performance lagging on major classes) for using the focal loss

TABLE III
FOCAL LOSS MODEL'S PARAMETERS AND FUSION WEIGHTS OBTAINED FROM FUSION MODEL

Activity	Gamma (γ)	Alpha (α_t)	Fusion Weight (CE Model)	Fusion Weight (FL Model)
A1	2	0.0487	0.27	0.73
A2		0.1385	0.19	0.81
A3		0.0148	0.67	0.33
A4		0.0045	0.54	0.46
A5		0.0011	0.61	0.39
A6		0.0014	0.41	0.59
A7		0.0001	0.47	0.53
A8		0.1604	0.08	0.92
A9		0.0985	0.12	0.87
A10		0.1685	0.19	0.81
A11		0.1837	0.25	0.75
A12		0.0353	0.48	0.52

is penalized using the fusion technique. The test accuracy of 1^{st} team is 22.35% of the competition [1]. The best accuracy of our proposed model on test data is about 34.47%, which beats the existing state-of-the-art work.

VI. CONCLUSION

In this paper, we have proposed a complex deep learning model architecture that can classify the nursing activities on the "Nurse Care Activity Recognition Challenge" dataset. Our methodology only uses the raw sensor data without doing any feature engineering. In the result section, it is noticeable that our proposed methodology does outstanding performance handling class-imbalance problems existing on the dataset. Our model can be further improved using complex architecture and various fusion techniques that can apply to other sensors domains. In the future, we will evaluate our model on the various sensor-based dataset to validate the robustness of our proposed architecture.

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