Multi-Class Weather Classification Using ResNet-18 CNN for Autonomous IoT and CPS Applications

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Abstract*— Severe circumstances of outdoor weather might have a significant influence on the road traffic. However, the early weather condition warning and detection can provide a significant chance for correct control and survival. Therefore, the auto-recognition models of weather situations with high level of confidence are essentially needed for several autonomous IoT systems, self-driving vehicles and transport control systems. In this work, we propose an accurate and precise self-reliant framework for weather recognition using ResNet-18 convolutional neural network to provide multi-class weather classification. The proposed model employs transfer learning technique of the powerful ResNet-18 CNN pretrained on ImageNet to train and classify weather recognition images dataset into four classes including: sunrise, shine, rain, and cloudy. The simulation results showed that our proposed model achieves remarkable classification accuracy of 98.22% outperforming other compared models trained on the same dataset.

***Keywords* — Weather conditions, ResNet-18, Convolutional Neural Network, Deep learning, Transfer Learning, Image Classification.**

I. INTRODUCTION

Nowadays, the weather detection models are essentially needed for several autonomous Internet-of-Things (IoT) and Cyber-Physical-Systems (CPS) such as driver assistance systems [1], self-driving vehicles [2], and transport control systems [3]. Traditional detection models for the weather conditions are usually developed by mounting a number of expensive sensors with the body of the system to calibrate the weather condition for the surrounding environment. Such design techniques provide is no escape for the system in case of "bad" weather detection. A more sophisticated models can be developed leveraging the power of cost-effective computer vision techniques by exploiting the existing surveillance cameras capturing images from the local environment to detect weather conditions [4]. Accordingly, several problems of the autonomous vision IoT/CPS systems (e.g. elements' damage, collisions and accidents, path loss, and others) can be avoided or mitigated if the weather conditions are detected and classification earlier. Consequently, weather detection system is significantly on-demand to be addressed for such systems to allow the systems to reconfigure their parameters and decisions for the various weather conditions.

To handle such critical image classification tasks, deep learning (DL) has evolved as a subset of artificial intelligence (AI) that does its inferencing using deep neural networks by employing the artificial neural networks with several layers among the input layer and output layer [5]. Currently, the deep learning (DL) models are gaining an appreciated amount of interest as almost all major IT companies are spending millions on the development and implementation of the intelligent solutions for wide range of applications especially those based on human thinking to provide a proper decision such as the image classification and prediction tasks [6].

Image classification (also called pattern recognition) techniques have been as widely applied in many real-life applications such image processing and analysis [7], natural language recognition [8], speech recognition [9], bio-metric identification and computer vision [10], seismic analysis [11], and radar signal classification and analysis [12]. Indeed, image classification using deep learning models has recently became a great interest of AI researchers especially with the hardware revolution of high-performance GPUs and the evolving of image classification competency namely know as ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2010. This in turn, has led for a number of advanced algorithms for object detection and image classification large scale [13], and thus, significantly optimized the implementation of the large and deep Convolutional Neural Networks (CNNs) [14].

CNN is multi-layer artificial neural network that implements the convolution operation in one or more of layers in order to learn distinct low-level and high-level features of the image [15]. The idea of CNN was firstly introduced by LeCun et al. [16] by introducing their LeNet-5 CNN to classify handwritten digits of MNIST dataset [17]. However, due to the lack of large training data and computing power at that time, their networks cannot perform well on more complex problems such as large-scale image and video classification [18]. Therefore, since that time and with the emergence of parallel GPUs as well as the evolution of big-data sets, the revolution of deeper CNNs have initiated to implement more complex classification and predication tasks. As results, several deeper and large-scale CNN architectures have been developed by the AI researchers such as $AlexNet$ [19], $VGGNet$ [20], $GoogleNet$ [21], $ZFNet$ [22] and $ResNet$ [23]. From the evolution of the architectures, $ResNet$ CNN introduced the residual learning framework to improve the training process of deep CNN networks which resulted in easier optimization of the network, and higher accuracy. ResNet won the champion of $ILSVRC$ 2015 and it is about 20 times deeper than $AlexNet$ and 8 times deeper than $VGGNet$ [18].

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In this paper, we are employing to use the residual CNN ResNet-18 to produce multi-class classification for weather condition images to help providing an early detecting of the weather conditions. The multi-class weather recognition dataset [24] stores a collection of 1125 images divided into four categories including sunrise, shine, rain, and cloudy. Based on the collected images, a ResNet-18 network is trained using transfer learning with several preprocessing stages, fine-tuning, and configuration. We show that the validation (testing) accuracy of the model is superior. In particular, the core contributions of the proposed work can be listed as follows:

- We provide an efficient classification model that employ the transfer learning technique for ResNet-18 CNN that is pre-trained with ImageNet dataset to learn the new features of the multi-class weather recognition dataset leveraging the power of our Nvidia GPU for parallel computation.
- We provide a comprehensive experimental results and analysis for the proposed classification model to provide more insight into the proposed method and solution approach. This includes simulation results related to the classification accuracy and error rate for training and testing, and the confusion matrix analysis, classification precision, as well as classification recall for the testing (validation) dataset.
- We provide benchmarking comparison of our results with existing up-to-date related research to show the advantage of the obtained findings.

The remainder of this paper is structured as follows: the next section, section II describes and discusses the system design modeling and architecture. Section III provides details about experimental environment, evaluation, and discussion. Finally, Section IV concludes the paper.

II. CLASSIFICATION MODEL USINGRESNET-18

Residual neural networks (ResNet) effectively allowed to train extremely deep NNs with even 150+layers successfully. Therefore, ResNet overcome the problems of vanishing gradients and degradation [25] resulted from the continuous increase in CNN's depth by introducing the residual blocks (RB) [5]. RB blocks introduce a "skip connection" that adds the output from the previous layer to the layer ahead to provide a fast-forward to a deeper layer as illustrated in Fig.1.

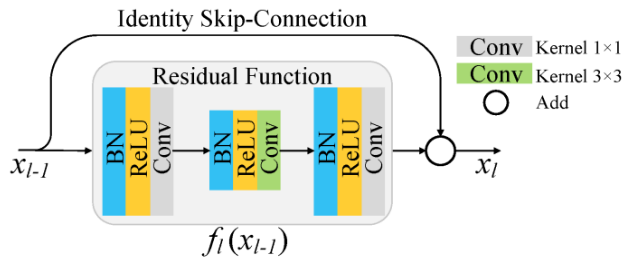

Fig. 1. Architecture of a residual block [26]

Normally, ResNet composed of a number of modules with four convolutional layers in each module. By configuring different numbers of channels and residual blocks in the module, we can create different ResNet models, such as ResNet-50 (has 50-layers), ResNet-152 (has 152 layers), or ResNet-18 (has 18 layers). Fig.2 shows the structure of ResNet-18. Together with the first convolutional layer and the final fully connected layer, there are 18 layers in total. ResNet-18 contains five blocks (modules): the 0th block is one single 3×3 convolutional layer, and each of the rest contains four 3×3 convolutional layers [27] .

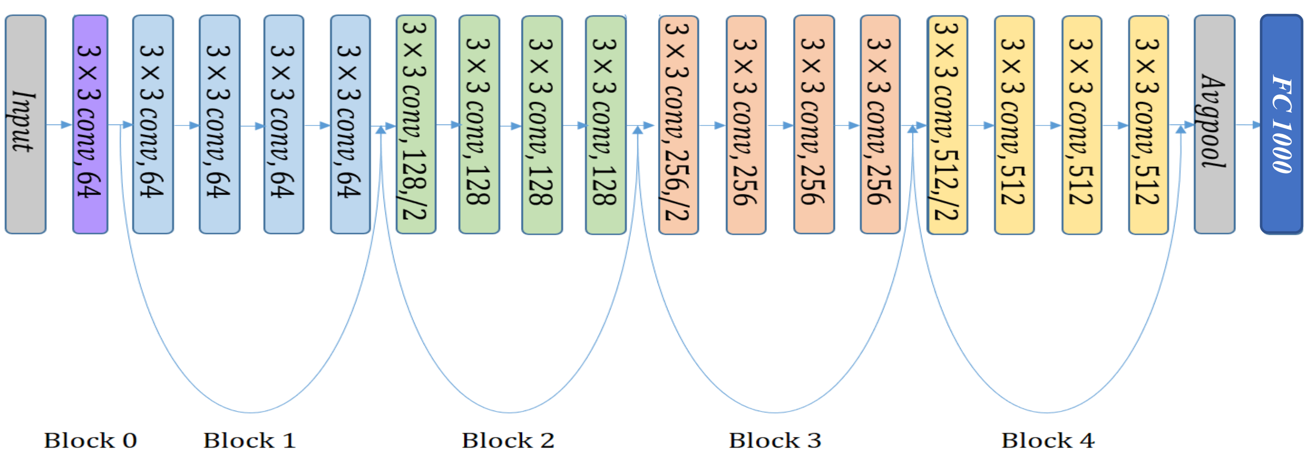

Fig. 2. The architecture of ResNet-18 [27]

In this work, the proposed classification model comprises three modules including: data collection and preprocessing module, Transfer learning based ResNet-18 module and Image classification module. The entire system framework exhibiting all implemented modules is illustrated in Fig. 3. The classification task begins from importing the image data from the collected weather condition datasets to the preprocessing stage, where the images-dataset undergoes into six processing operation priors being used at the training/testing of the ResNet-18 CNN. All processing stages are explained in the upcoming subsections.

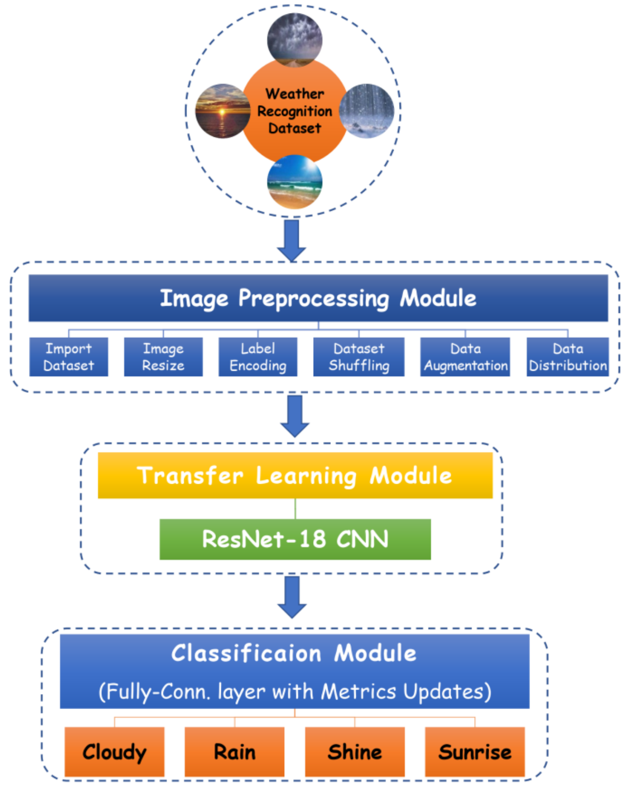

Fig. 3. Proposed data flow diagram for the system modules

2.1 The Dataset "Weather Recognition Dataset"

In this paper, we are utilizing the multi-class weather recognition dataset (MCWRD) [24] to develop an automatic and self-reliant recognition scheme that can be used to provide multi-classification of the outdoor weather condition images into four categories including: cloudy, rain, shine, and sunrise. MCWRD is an up to date (published in 2018) and publicly available dataset. It is a comprehensive dataset composed of 1125 colored images with different image dimensions and bit-depths. The image distribution of the dataset categories is provided as: Cloudy (300 images), Rainy (215 images), Shine (253 images), and Sunrise (356 images). Also, samples images for the different weather conditions of the dataset are provided in Fig. 4.

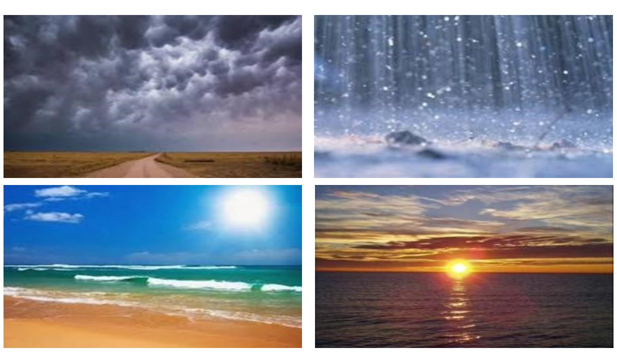

Fig. 4. Sample Images (a) Cloudy (b) Rainy (c) Shiny (d) Sunrise.

2.2 Image Preprocessing Module

Commonly, image preprocessing operations is significant stage for any image classification application. They are performed over the original images of the dataset to prepare the images to be fed into the neural network model such as ResNet-18 in this work. Therefore, the collected dataset images are preprocessed as follows:

Import Dataset: This operation is responsible to read the dataset images from the local hard drive into datastore for image datatype in MATLAB platform (i.e. *ImageDatastore* object). *ImageDatastore* can manage a collection of image files with categorization where each class name is derived from the folder holding its corresponding images.

Image Resize: This operation is responsible to unify the image dimensions and depth for all images in the dataset to accommodate the input size for the ResNet-18. Thus, we have developed a MATLAB function to convert all images into 3D matrices (RGB images) with image dimension of 224 x 224 x 3 all with JPG image extension.

Label Encoding: This operation is responsible to encode the categorical labels into numerical labels to be understood by machine learning models. Therefore, we have used the integer encoding technique to end up with four labels as follows: cloudy:1, rainy:2, shiny:3, and sunrise:4.

Dataset Shuffling: This operation is responsible to randomly rearrange the dataset images to enhance the classification by generating unbiased distribution of the dataset which avoid model biasing toward specific class(s).

Data Augmentation: This operation is responsible to effectively increase the amount of training data by applying randomized augmentation operations on the dataset. Augmentation process configures a set of preprocessing options such as resizing, cropping, rotation, reflection, invariant distortions, and others.

Data Distribution: This operation is responsible to randomly split the dataset into training set and testing (validation) set. To ensure high level of unpredictability, random-cross validation process to examine the accuracy of the model at different distributions of dataset.

2.3 Transfer learning Module

This module is responsible of feature extraction and learning to accomplish a particular image classification application. However, with the transfer learning technique, there is no need to perform the long-time training process from scratch for the new classification task, instead, it's possible to use any well-known deep neural network that is pretrained on a specific dataset to perform new classification tasks, but with fine-tuning for the learning parameters. As reported in [28], transfer learning is an optimization, a shortcut to saving time or getting better performance. Fig. 5 demonstrates the idea of transfer learning. According to the figure, the learning parameters for the generic CNN at (A) is transferred to do the new task at (B). At task (B), all required is to customize the input and output layers only (fine-tuning).

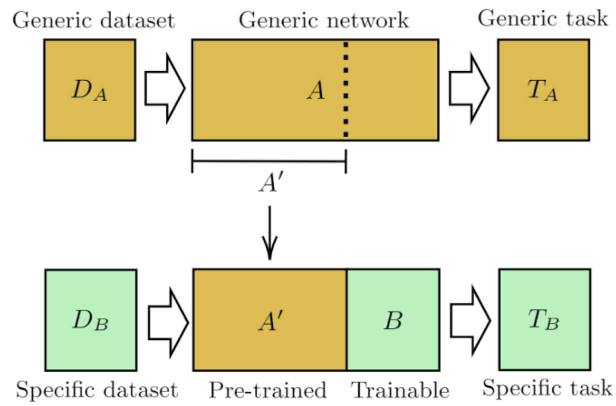

Fig. 5. Demonstration of Transfer learning concept [29].

In this work, we have applied the transfer learning mechanism by fine-tuning the network parameters and output layer for the robust ResNet-18 CNN by adopting the pretrained parameters of ResNet-18 from ImageNet dataset [24].

2.4 Classification Module

This module is responsible of categorizing the collected dataset into different classes for the purpose based on the recognized or extracted patterns or features. A classification module utilizes a fully connected layer and computes the cross-entropy loss for multi-class classification problems with mutually exclusive classes [6]. For better demonstration for the classification module, we show the connection layers of the is module in Fig.6.

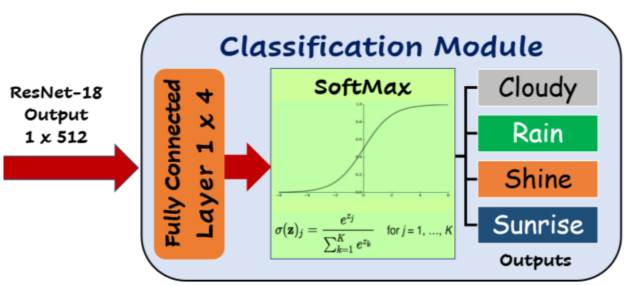

Fig.6. Demonstration of Image Classification Module.

According to the figure, Fig.6, this module obtains the high-level features extracted from ResNet-8 CNN within a fully connected (FC) NN of size 512 x 4 neurons. This will result into four outputs are processed through SoftMax activation to provide the probabilities for the four classes of the four neurons. $SoftMax$ is probability distribution function that assigns numerical probabilities to each class in a multi-class problem [30]. Those numerical probabilities must add up to one.

An example of a classification test for $rainy$ image using our implemented model using $Softmax$ activation function could generate the probabilities of an image belonging to a particular class as illustrated in Fig. 7.

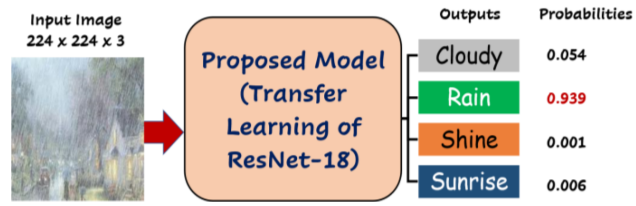

Fig.7. Example of a classifying "Rainy" image.

Moreover, the training and validation losses has been computed using $Mean\ Squared\ Error\ (MSE)\ loss$ [6] while optimized using Root Mean Square Propagation optimizer (RMSprop) [31].

III. Experiment Setup and Results

The aforementioned model has been implemented using MATLAB along with the associated deep learning toolbox to enable the utilization of deep neural network (e.g. different CNNs) with their corresponding algorithms as well as the parallel computation toolbox to enable the utilization of GPU component. Also, to validate the system performance, we have split the collected weather conditions dataset randomly by using ${}^{3}/_{4}$ of the dataset for the training set and using ${}^{1}/_{4}$ of the dataset for the validation (testing) set. Moreover, we summarize the complete configurations for the development environment in Table I.

Table. I. Development Environment Configurations

Development Items	**Description**
Training/Testing Model	Transfer Learning via ResNet-18
Optimization Technique	Stochastic Gradient Descent (SGD)
Multi-Classifier technique	Onevsall (one-vs-All classification)
Classification Learner	Linear learner algorithm
Validation Frequency	5-Fold Cross Validation
Max number of Epochs	25
No. of iterations per Epoch	84
Mini Batch Size	10
Initial Learning Rate	0.0001
Shuffle Frequency	Every Epoch

Also, to measure the system performance, we have evaluated the developed classification model in terms of several evaluation metrics [32] including the following:

- Multi-Class Confusion Matrix ($\boldsymbol{CM}$) is used to describe the performance of a multi-class classification model in terms of True Positives ($\boldsymbol{TP}$), True Negatives ($\boldsymbol{TN}$), False Positives ($\boldsymbol{FP}$), and False Negatives ($\boldsymbol{FN}$).

- Classification Accuracy ($\boldsymbol{CA}$) is calculated as the ratio of the number of correct classifications to the total number of classifications ($\boldsymbol{CA} = (\boldsymbol{TP} + \boldsymbol{TN})/(\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN})$)
- Misclassification Rate, also known as Classification Error ($\boldsymbol{CE}$): is calculated as the fraction of predictions were incorrect. ($\boldsymbol{CE} = \mathbf{1} - \boldsymbol{Accuracy}$).
- Classification Precision ($\boldsymbol{CP}$) is the ratio of the correctly positive labeled by the classifier to the total number of all positive labels ($\boldsymbol{CP} = \boldsymbol{TP}/(\boldsymbol{TP} + \boldsymbol{FP})$).
- Classification Sensitivity ($\boldsymbol{CS}$) is the ratio of all positive samples were correctly predicted as positive by the classifier ($\boldsymbol{CS} = \boldsymbol{TP}/(\boldsymbol{TP} + \boldsymbol{FN})$).

Moreover, Fig.8 illustrates the classifier performance plots for both the training and validation sets in terms of classification accuracy and classification loss for 25 epochs. Besides, the figure also presents the confusion matrix for the validation set showing the confusion factors $\{(TP), (TN), (FP), (FN)\}$ for the dataset classes $\{(C1\colon Cloudy), (C2\colon Rain), (C3\colon Shine), (C4\colon Sunrise)\}$. According to the figure, both evaluation metrics (i.e. accuracy and loss) are uniformly proceeding along with the progressing of training epochs with decremental inclination for the loss function toward the zero MSE and incremental trend for the accuracy function toward the 100%. However, both metrics have almost saturated after almost 13 epochs with error less than 0.05 of MSE and accuracy more than 98%. In addition, based on the confusion matrix, were able to calculate the aforementioned evaluation metrics and the obtained results can be summarized as follows:

$$\boldsymbol{AC} = \mathbf{98.22}\%, \qquad \boldsymbol{CE} = \mathbf{01.78}\%,$$
$$\boldsymbol{CP} = \mathbf{96.5}\%, \qquad \boldsymbol{CS} = \mathbf{96.4}\%.$$

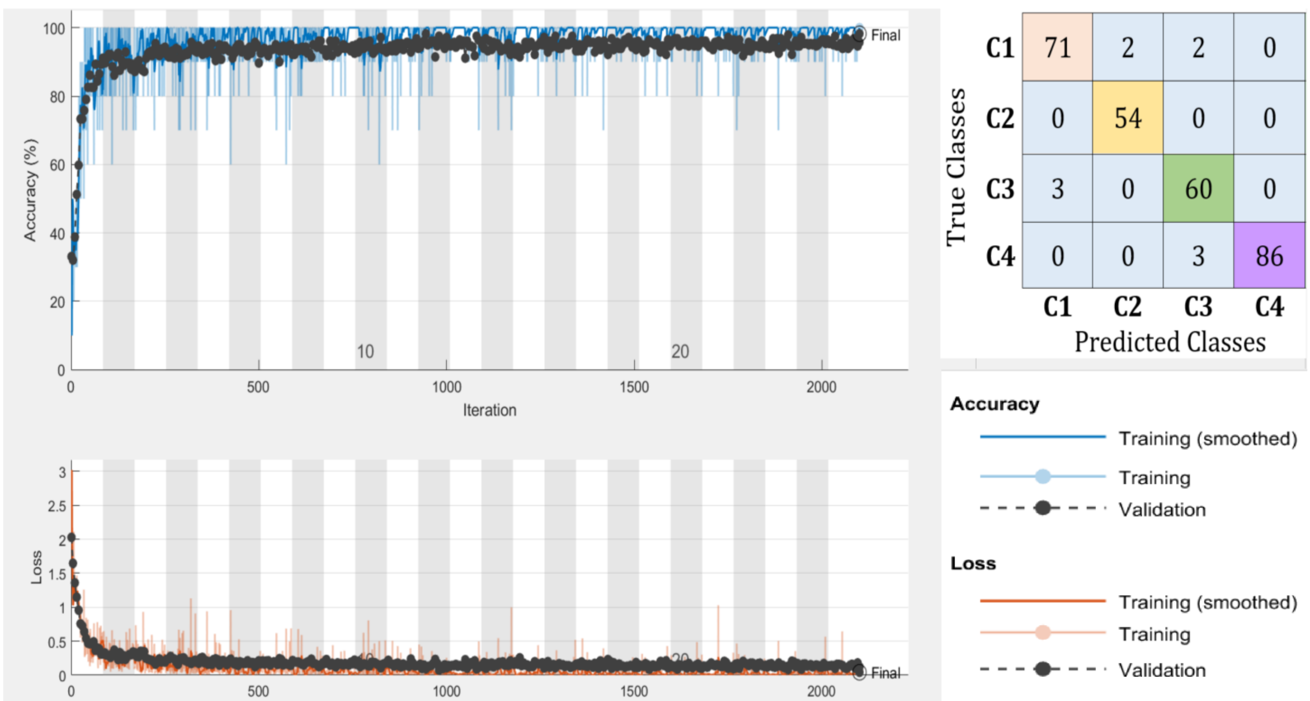

Fig. 8. (a) Training/Testing Accuracy/Loss vs. number of epochs (b) Confusion Matrix and Summery of Evaluation metrics

Finally, even though the exiting state-of-art researches for classifying the weather conditions dataset use different network configurations, learning policies, programming techniques, and computing platforms, however, we still can compare the classification system performance in terms of training and testing accuracy metrics. Therefore, for better readability, we summarize the time accuracy metrics for related state-of-art research's in the following table, Table II, in chronological order. According to the comparison of the table, it can be seen that our proposed model has recorded an attractive result in terms of both training and testing accuracy showing superiority over all other compared methods.

TABLE. II. COMPARISON WITH EXISTING RELATED WORK METHODS

Research Method	/ Year	Accuracy (%)	Enhancement %
C. Zheng et. al.	[4] / 2016	94.00 %	≈ 105%
W. Chu, et. al.	[33] / 2017	96.30 %	≈ 102%
Z. Zhu et. al.	[34] / 2017	95.46 %	≈ 103%
Y. Shi et. al.	[35] / 2018	94.71 %	≈ 104%
L. Kang et. al.	[36] / 2018	92.00 %	≈ 107%
O. Luwafemi et. al.	[37] / 2019	86.00 %	≈ 114%
M. Ibrahim et. al.	[38] / 2019	97.69 %	≈ 101%
Y. Wang et. al.	[39] / 2020	81.25 %	≈ 121%
J. Xia et. al.	[40] / 2020	96.03 %	≈ 102%
Proposed Model	/ 2020	**98.22** %	——

IV. Conclusions

A reliable auto-recognition deep-learning model to classify the weather condition images with high-level of classification accuracy, precision, and recall. To enhance the performance of feature extraction and learning, we have utilized the power of transfer learning technique with fine-tuning of the recognized deep ResNet-18 CNN pretrained on ImageNet dataset. The developed model uses the multi-class weather recognition dataset with 75% of the images used for training and 25% used for testing. Actually, the proposed work provides an inclusive framework model for multi-class image classification applications from input layer to the output layer. Finally, based on the comparison with other related research in the field, the obtained results outperform the results of existing automated classification models for weather conditions images.

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