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Residual Network Architecture Model for Image Weather Classification

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A B S T R A C T

Weather classification plays an important role in many fields, including agriculture, transportation, and meteorology. Traditional methods for weather recognition are usually based on human observation or sensor networks, which are prone to errors and quite costly. To overcome the limitation, this research implements the Convolutional Neural Network method with a Residual Network model architecture for image-based weather classification. Using a dataset of 1,500 images categorized into five weather conditions cloudy, foggy, rainy, sunny and sunrise. The model training accuracy reached a level of 92%, while the validation accuracy reached a level of 94% and resulted in a testing accuracy of 86.7%. The model training accuracy was high for sunny and sunrise conditions. Accuracy was lower in rainy and foggy weather conditions. This research shows that the ResNet model architecture can provide a low-cost, efficient, and high-accuracy solution for weather classification.

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1. INTRODUCTION

Many aspects of human endeavour such as social, economic, agricultural and environmental conditions are greatly influenced by the role of weather. In daily activities, for example wearing clothes, outdoor events, travelling, transportation and solar technolog [1], [2]. Weather is an important factor in determining the outcome of agricultural endeavours [3] . Agricultural planning can be optimized with accurate weather classification [4]. In addition, weather has a major impact on urban traffic, some weather conditions can reduce visibility and make roads slippery [5]. To improve driving safety, automatic weather recognition of road conditions is essential in traffic management and automobile auxiliary driving [5], [6], [7]. Most importantly, meteorologists need a classification of weather phenomena to improve the quality of weather predictions and knowledge of climate conditions [4].

Considering this need, weather recognition or classification is necessary for the meteorological discipline and many other facets of life. However, traditional methods based on human observation are time consuming and prone to errors [4]. futhermore, method based on sensor networks are costly and inefficient [5],[8],[9]. Due to the limitations of traditional methods, it is crucial to develop more efficient, accurate, and low-cost weather recognition methods. The recent development in computer vision technique enabled weather recognition through image processing [1], [2], [8] , increasing, efficiency and cost effectiveness [9].

In this paper, we aim to build a weather classification model using CNN method with Residual Network (ResNet) architecture, the dataset used consists of 1500 weather images. The model we built will classify the image into 5 weather conditions including cloudy, foggy, rainy, sunny, and sunrise. Before training, data augmentation is carried out first, after training, validation will be carried out. This research is expected to be able to create a classification technique that is cheap, efficient and high accuracy.

2. RELATED WORK

There are several machine learning algorithms used for classification including CNN (Convolutional Neural Networks), SVM (Support Vector Machine), and KNN (K-Nearest Neighbors). Ship et al research used the SVM method in classify 4 weather conditions with an accuracy of 92.8% [10]. The K-NN algorithm was applied for extreme rainfall estimation on 24 December, 2020 between CCTV camera image data and AWS resulting in an accuracy of 94%[11]. Xiao et al in their research classified 11 weather phenomena using an algorithm architecture called MeteCNN with accuracy performance achieving 92.68% [4]. Then Xia et al using the CNN method with an architecture called ResNet15 with additional data augmentation was able to classify 4 weather conditions with 96% accuracy [5].

Convolutional Neural Network (CNN) is a deep learning algorithm that is widely used for visual recognition of objects. The structure of CNN is generally divided into 3 sections: input layer, hidden layer and output layer [12]. The hidden layer consists of convolutional layer, rectified linear unit (ReLU) layer, pooling layer and fully connected layers[13]. The CNN is based on linear algebra represented by matrix vector multiplication used to represent data and weights[14]. The convolution layer functions for feature extraction which is carried out by several convolution kernels, each kernel extracts features from its input map. The amount of convolution kernels can be set according to the preference of the user model, the number of features extracted will be directly proportional to the number of kernels arranged. The pooling layer functions to reduce parameter size and computation, thus reducing the effect of overfitting. ReLU makes the negative value zero, increasing the model's non linearity[15]. Deep stacking is the process of repeating the convolution, pooling, and ReLU steps in several layers. The fully connected layer functions to deliver the classification decision[13]. In its application, CNN has various architectural developments, such as VGGNet, ResNet, DenseNet, etc., each of which has a model design to improve accuracy in various problems in visual object recognition.

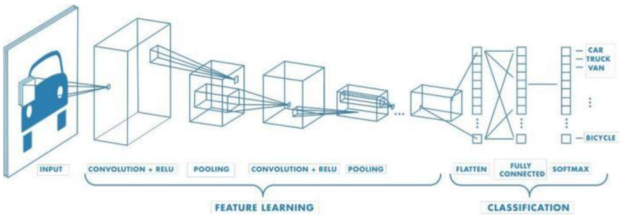

Fig. 1.1 Convolutional Neural Network Architecture [16]

VGG Network is architecture of CNN proposed by the Visual Geomety Group (VGG) of Oxford University in 2014 released in a paper by Simonyan and Zisserman. VGG network shown in Figure 2, that the depth of the network is useful for image recognition, uses small (3x3) convolution filters that show significant improvement when going into 16-19 weight layers [17]. The VGG Network architecture consists of convolution and max pooling layers for feature extraction, as well as a fully connected layer for image classification [18][19]. Network receives an input image of size 224x224, the average RGB value is subtracted from each pixel of the training set image in preprocessing. Each image goes through a 3x3 convolution filter stack with convolution stride is 1 pixel. The convolution layer consists of 5 parts which are always followed by a max-polling layer and the window size is 2 × 2 and the step size is 2. Then the image goes through 3 fully connected layers with layers 1 and 2 have 4096 channels and layer 3 have 1000 channels and the final is the soft-max layer [15][17][19].

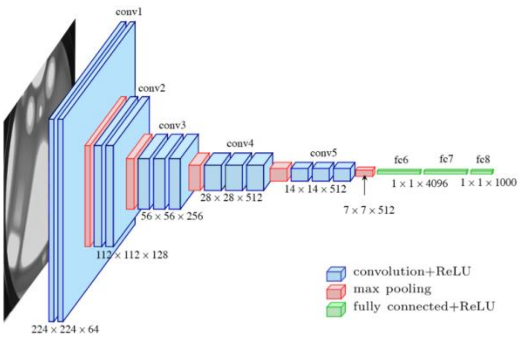

Fig. 1.2 VG6 Network Architecture by K. Simonyan and A. Zisserman [18]

Densely Connected Convolutional Network was originally proposed by Huang et al. from Cornell University in 2017 [20] which achieved state-of-the-art results on image classification with datasets named Cifar-10 and SVHN. There is a problem of gradient loss and model degradation when there are a large number of layers of convolutional neural network architecture. Dense Convolution Network provides a solution by connecting directly from all layers to all next layers. Each layer takes the output of all previous layers as input, and its own output as input of each next layer [20]. DenseNet has the advantage of smaller model parameters and computations, compact internal representations, reduced feature redundancy, and overcoming gradient loss and model degradation [21].

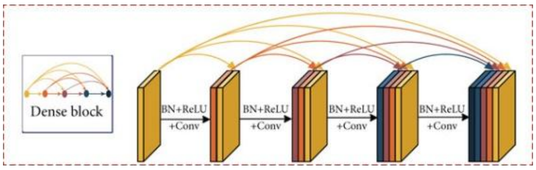

Fig. 1.3 Dense Block Model

Kaiming He et al. of Microsoft Research introduced the Residual Network in a journal article published in 2015 [23]. Networks modelled with significant deepness exhibit a strong capacity for nonlinear learning. The gradient of each layer in the network is trained in relation to the previous layer. As the number of layers in a multi layer neural network increases, so does the model error due to gradient disappearing [24]. The introduction of residual network offers an innovative solution to the problem of gradient disappearing [23]. Residual network bypasses the standard feedforward neural network of adding inputs to the output, This approach supports data integrity, simplifies the learning process, and minimizes the risk of increased training error due to number of layers deepens [21].

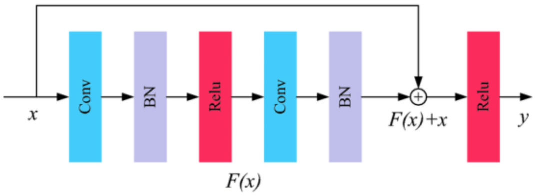

Fig. 1.4 Residual Block Structure

3. RESULTS

3.1 Data

Data serves as the crucial element for deep learning algorithms, particularly in the context of weather recognition. The effectiveness of deep neural network recognition is greatly influenced by the size of the datasets used [25]. In performing classification, supervised machine learning earning requires a large collection of labeled data [4]. This research uses a dataset that is available on the kaggle website which can be accessed at https://www.kaggle.com/datasets/vijaygiitk/multiclass-weather-dataset.

Fig. 3.1 Example Weather Images in the Dataset

The dataset has a total of 1500 images which are divided into 5 conditions, namely cloudy, foggy, rainy, shine and sunrise shown in Figure 5. Furthermore, the dataset is divided into training data and validation data with a division of 0.85 for training and 0.15 for validation, the distribution of training data is shown in Figure 6 and training data in Figure 7. The augmentation stage is carried out first before the data is trained. Augmentation data is proven to improve classification accuracy based on research conducted by Jingming Xia et al [5]. This time the augmentation process carried out is rescale, rotation, zoom, and horizontal flip.

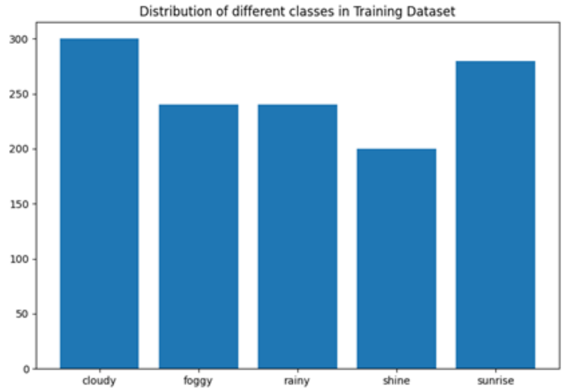

Fig. 3.2 Distribution Classes of Training Dataset

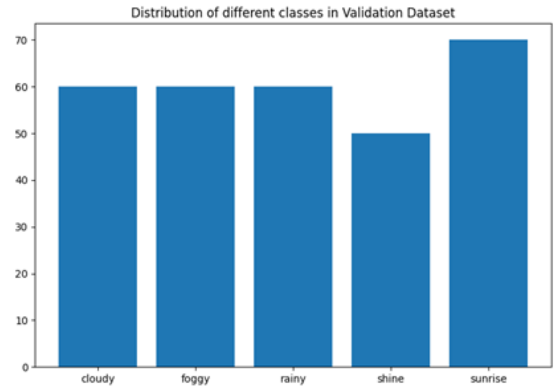

Fig. 3.3 Distribution Classes of Validation Dataset

3.2 Architecture Model

Figure 3.2 shows the average monthly rainfall during the study period.

We apply CNN method with residual network architecture to perform weather classification. The classification process goes through several layers shown in Table I , starting at the convolution layer has 64 filters, a kernel of size 7x7, and a stride of 2, functioning in extracting initial features from the input image. Followed by batch normalization layer to stabilize the value distribution and max pooling layer with 3x3 kernel and stride of 2 to reduce the spatial dimension and computational load. Then, the feature extraction process goes through six residual blocks.

Table 1. Architecture ResNet

Layer Type	**Details**	**Output Shape**
Input Layer	-	(None, 256, 256, 3)
Conv2D	64 filters, 7x7 kernel, stride 2, ReLU	(None, 128, 128, 64)
BatchNormalization	Normalization	(None, 128, 128, 64)
MaxPooling2D	3x3 pool, stride 2	(None, 64, 64, 64)
Residual Block 1	2x (64 filters, 3x3 kernel, stride 1)	(None, 64, 64, 64)
Residual Block 2	2x (64 filters, 3x3 kernel, stride 1)	(None, 64, 64, 64)
Residual Block 3	2x (128 filters, 3x3 kernel, stride 2/1)	(None, 32, 32, 128)
Residual Block 4	2x (128 filters, 3x3 kernel, stride 1)	(None, 32, 32, 128)
Residual Block 5	2x (256 filters, 3x3 kernel, stride 2/1)	(None, 16, 16, 256)
Residual Block 6	2x (256 filters, 3x3 kernel, stride 1)	(None, 16, 16, 256)
GlobalAveragePooling	Pooling over spatial dimensions	(None, 256)

Dense	512 units, ReLU	(None, 512)
Dense (Output)	5 units, Softmax	(None, 5)

Each residual block is composed of several layers shown in Table II, that is tw0 convolution layers accompanied by batch normalization and ReLU activation function. To ease the gradient flow during training, these blocks are equipped with shortcut connections that connect the initial input of the block to the output of the last convolutional layer. After passing through all the residual blocks, the global average pooling layer reduces the spatial features to a 1-dimensional vector with 256 elements output. The vector is then passed to the fully connected layer that outputs 512 units and ReLU activation to generate a feature representation, before finally being processed by the output layer that has 5 neurons with softmax activation function to generate classification probabilities to the five weather condition classes.

Table 2. Layer of Block Residual

Layer Type	**Details**	**Output Shape**
Conv2D	128 filters, 3x3 kernel, stride 2, ReLU	(None, 32, 32, 128)
BatchNormalization	Normalization	(None, 32, 32, 128)
Activation	ReLU	(None, 32, 32, 128)
Conv2D	128 filters, 3x3 kernel, stride 1	(None, 32, 32, 128)
BatchNormalization	Normalization	(None, 32, 32, 128)
Shortcut Connection	Conv2D (1x1, stride 2) + Add	(None, 32, 32, 128)
Activation	ReLU	(None, 32, 32, 128)

4. RESULT AND DISCUSSION

A Residual Network (ResNet) model was successfully built for image-based weather classification. The model classifies five weather conditions cloudy, foggy, rainy, shine, and sunrise, with a dataset consisting of 1,500 images. Following the training process, the model achieved a training accuracy of 92% and validation accuracy of 94%. Figure 8 shows the training and validation accuracy for each epoch, highlighting the overall performance and suitability of each model. It shows the consistency in accuracy between the training and testing curves with no overfitting occurring. As seen in Figure 9, the training and validation loss values are low. The steady decrease in validation loss indicates that the model has good generalisation to unencountered data.

Fig. 4.1 Accuracy of Training and Validation

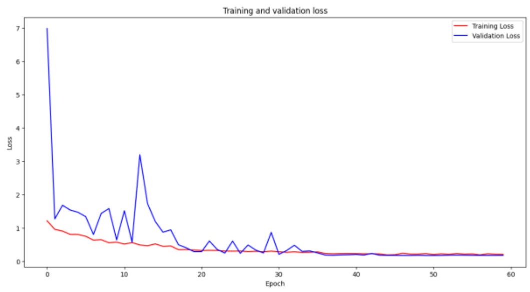

Fig. 4.2 Loss of Training and Validation

The Residual Network has the main idea of simplifying the training of very deep networks by using shortcut connections that pass information directly to the next layer, shown in Figure 4. Serving to prevent deep-level weather characteristics extracted by the convolutional layer during transmission and damage, six blocks of residual are incorporated into the model. The weather characteristics extracted in the previous layer serve as a shortcut through the residual module to the next layer, improving the convergence rate of the network model, improving the recognition accuracy, and solving the vanishing gradient problem caused by the larger network depth.

Model was programmed to train with 100 epochs, but the training stopped when the epoch reached 60. The training stopped because the EarlyStopping callback detected that the validation loss had reached the optimal point. This is indicated because there is no more significant improvement in the last 10 epochs. This mechanism prevents over-fitting and reduces training time.

The model was tested with 30 test images as shown in Fig. 10, the model produced accurate predictions for 26 images, while the remaining 4 images were incorrectly classified. This gives an accuracy rate of 86.7% on the test data. Based on the confusion matrix, the shine and sunrise conditions have perfect prediction accuracy, showing the strength of the model in recognizing these two conditions. However, some errors occurred in conditions such as rainy and foggy.

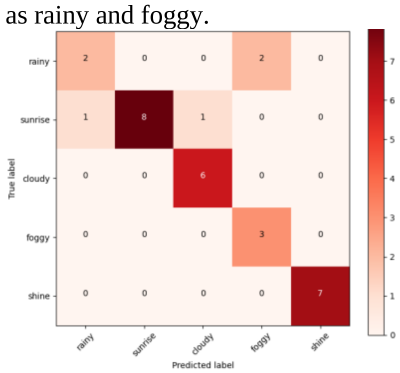

Fig. 4.3 Confusion Matrix

Value of testing accuracy is lower than the training and validation accuracy. We estimate this is because the testing dataset is too small, such as in rainy and foggy which are only 4 and 3. So that the testing data has not drawn the true testing accuracy. To see the smallness of our test dataset, we will compare it with other similar studies. Separated WEAPD (6877) into 8:1:1 training, validation, and testing groups [4]; 8000 training images and 2000 testing images [26]; split the dataset (23865) 80% for training and 20% testing [27].

5. CONCLUSION

In this study, a low-cost, efficient, and high-accuracy image-based weather classification technique using the Residual Network (ResNet) model was successfully built. This model can classify images into 5 weather conditions, including cloudy, foggy, rainy, shine, and sunrise, using a dataset of 1500 images. The training accuracy of the model is 92% and the validation accuracy is 94%, showing good performance and consistency between the training and validation data. Testing was conducted with 30 test images, where the model successfully classified 26 images correctly and 4 images were incorrectly classified with a testing accuracy of 86.7%. The accuracy of the model was very good in shine and sunrise conditions, but low classification accuracy results in rainy and foggy conditions. Testing accuracy can be improved to similar to training and validation accuracy by increasing the number of images in the test dataset.

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