WEATHER IMAGE CLASSIFICATION BASED ON COMBINATION OF CNN AND XGBOOST

Tran Quy Nam and Vu Huu Tien
Posts and Telecommunications Institute of Technology

Abstract: This study proposes to test a combination model between CNN network and XGBoost algorithm for weather image classification problem. The proposed model uses deep learning network, namely CNN for feature extraction, then feeds the features into the XGBoost classifier to recognize the images. The model applies a test dataset which is a set of 11 different image classes collected under different weather patterns. The same dataset is also tested with other deep learning networks including Xception, InceptionV3, VGG19, VGG16 according to the general principle of parameters, keeping the original image for comparison. The test results show that the CNN-XGBoost model gives the best accuracy results, suitable for application in evaluating and classifying photos describing different types of weather.

Keywords: CNN, XGBoost, photo, weather.

I. INTRODUCTION

Application of image processing in weather assessment and forecast is an important field in human life and socio-economic development. The problem of weather image processing also plays an important role in forecasting and analyzing the effects of weather in the field of security and defense. In fact, there have been many studies on processing and analyzing weather images using machine learning techniques, deep learning... applied in the development of self-driving cars, intelligent traffic systems.

Accurate processing and identification of weather photos taken from satellites or weather observation stations is an important method in weather forecasting, warning consequences, severity of natural disasters, weather conditions, and weather conditions or bad weather. The process of monitoring and analyzing satellite cloud images is a highly effective method for weather forecasting and warning through a high-resolution satellite cloud image acquisition system. Weather photo analysis helps to assess the actual situation, factors that have positive or negative impacts on socio-economic activities such as agriculture, forestry, fisheries, tourism, etc. At the same time, it helps the weather forecasters actively monitor, analyze and detect dangerous weather phenomena and dangerous weather systems affecting human life.

Recognizing weather phenomena that significantly affect many aspects of our daily lives, such as weather forecasting, road condition monitoring, transportation, agricultural and forestry management and natural environment detection. In contrast, very few studies have attempted to categorize images of actual weather phenomena, often relying on visual observations from humans. To our knowledge, traditional man-made visual distinctions between weather phenomena are time-consuming and error-prone. Although some studies have improved the accuracy and efficiency of weather phenomenon recognition using machine learning, they have identified fewer types of weather phenomena.

In autonomous vehicle control, the correct identification of photos to assess the weather situation and make decisions about operating the operating mode of the traffic vision assist system or ADAS (advanced driver assistance system) play an important role. At the same time, the weather image recognition problem contributes to analysis and gives meaningful information on some other outdoor monitoring systems.

Researching weather image recognition in computer vision helps build weather biometric devices that sense and interpret weather conditions through image data. During the driving process, being aware of extreme outdoor weather patterns can have a significant impact on road traffic safety. Through the analysis of weather images, it helps to detect bad conditions early and warn drivers. At the same time, highly reliable automatic recognition of weather situation images provides valuable information for automated IoT systems, self-driving vehicles, and vehicle control systems.

Thus, the problem of automatic and high-quality image classification of weather phenomena can provide a reference for future studies on weather image classification, disaster prediction and weather forecast.

Contact author: Tran Quy Nam
Email: namtq@ptit.edu.vn
Manuscript received: 3/2023, revised: 5/2023, accepted: 7/2023.

Therefore, this study proposes a model that uses a combination model of VGG16 (based on CNN) with XGBoost algorithm to classify weather photos. The reason for choosing XGBoost is because it is a relatively new algorithm and has a fast processing speed. Experimental results will be compared with some other traditional models and presented in the next sections.

II. LITERATURE REVIEW

In fact, there have been many studies using machine learning models, deep learning to identify weather photos around the world. One of them is a study conducted by Kang et al [1] with image data captured from outdoor visualization devices using a deep learning based weather image recognition framework by considering the three most common weather conditions, including fog, rain, and snow, in outdoor scenes. The results of extensive tests based on two GoogLeNet and AlexNet networks, conducted on the weather image data set, gave good results and high feasibility. Mohammad et al. [2] performed a study aimed at classifying weather images using a CNN network with transfer learning. Four architectures CNN, MobileNetV2, VGG16, DenseNet201 and Xception are used to perform weather image recognition and classification. Transfer learning is used to speed up the model training process to get better performance and run faster. The proposed methods are applied to weather images including six layers, cloudy, rainy, sunny, sunrise, snowy and classified fog. The test results show that Xception has the best average accuracy of 90.21% with an average training time of 10,962 seconds and MobileNetV2 has the fastest average training time of 2,438 seconds with an average accuracy is 83.51%.

Haixia et al [3] conducted research to build a new deep neural network (CNN) named MeteCNN to classify weather phenomena. Meanwhile, the study uses a weather phenomena dataset (WEAPD) containing 6,877 images with 11 weather phenomena, which has more categories than the previous dataset. The classification accuracy of MeteCNN on the WEAPD test suite is about 92% (with image augmentation), and the test results show the superiority and efficiency of the MeteCNN model. Mohamed et al [4] introduced a model that automatically extracts weather information from photographs based on deep learning and computer vision. WeatherNet model is trained, based on transfer learning using ResNet50 network architecture to extract weather information and different images such as sunrise, sunset, day and night, rain, snow and fog for different weather conditions. WeatherNet shows good performance in extracting weather information from user-defined images or from video streams with weather images.

In the paper of Elhoseiny et al. [5], the authors studied weather classification from images using CNN network combined with transformation learning. The authors' approach based on the Weather-CNN network with ImageNet-CNN gives good results compared to some other methods in the weather classification problem. The authors' approach achieves a standardized classification accuracy of 82.2% instead of 53.1% for the other method.

Manthan et al. [6] classified images of weather patterns using convolutional neural networks and deep learning algorithms. The results show that the classification model is quite good, proving that it can combine image recognition capabilities, allowing weather classification of certain input images, such as sunshine, rain,... Qasem et al. [7] studied weather image classifier recognition using ResNet-18 neural network to provide weather image classification. The model uses transfer learning technique based on ResNet-18 that has been pre-trained on ImageNet image set to train and classify the weather recognition image dataset into four classes including: sunrise, sun morning, it was raining and it was cloudy. Research results show that the proposed model achieves a remarkable classification accuracy of 98.22% which is superior to other types of models trained on the same data set.

The above studies have high accuracy by using many new weather imaging techniques from the available data set (image augmentation), combined with techniques to refine model parameters. While the research in this paper uses the original image, does not generate new images by rotating, flipping, etc. to ensure the authenticity in comparing the deep learning models. At the same time, the applied model will freeze the training parameters and only use the original model for the weather image classification problem.

III. METHODOLOGY

A. Proposed model for research

This study proposes a model using a convolutional neural network (CNN) trained VGG16 for feature extraction and the XGBoost algorithm for classification and they are both applied into the classification of the classes of weather images (see Figure 1). To unify the comparison parameter, the images are uniformly sized before being fed into the training and classification models.

XGBoost algorithm stands for Extreme Gradient Boosting, a highly efficient machine learning algorithm based on a combination of techniques to adjust error weights on weaker models to create a stronger model. XGBoost algorithm principle is based on decision tree and gradient enhancement technique to give the optimal model. Sequentially generated new trees minimize the error from the previous tree by relearning the error of the previous tree, performing error correction to get a better tree. XGBoost was originally introduced by Chen and

Guestrin (2016) to improve the performance and speed of decision trees by the principle of gradient enhancement (gradient-boosted) [10].

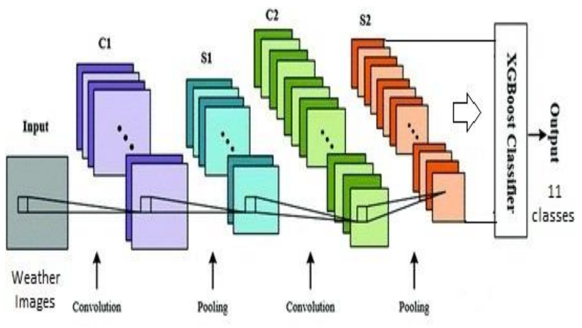

Figure 1: CNN-XGBoost Network Architecture

According to the description of the XGBoost algorithm given by authors of Chen and Guestrin [10], XGBoost works as follows:

For a given dataset with n samples and m features $D = \{(x_i, y_i)\}$ $(|D| = n,\ x_i \in R^m,\ y_i \in R)$, apply a model that combines the tree uses K enhancement functions to predict the output.

$$\hat{y}_i = \emptyset(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in F \quad (1)$$

where $F = \{f(x) = w_q(x)\}$ $(q : R^m \rightarrow T,\ w \in R^T)$ is the space of the regression tree (also known as CART). Here q is a representation for the structure of each tree, mapping a data sample to the corresponding leaf index. T is the number of leaves on the tree. Each f_k corresponds to an independent tree structure q and leaf weight w.

To find out the set of functions used in the model, the following normative objective function minimization algorithm:

$$\mathcal{L}(\emptyset) = \sum_{i=1}^{n} l(\hat{y}_i, \mathrm{y}_i) + \sum_{k}^{K} \Omega(f_k) \quad (2)$$

$$\text{where } \Omega(\mathrm{f}) = \gamma \mathrm{T} + \frac{1}{2}\lambda||\mathrm{w}||^2$$

Where, l is a differentiable convex loss function used to measure the difference between the predicted value $\hat{\mathbf{y}}_\mathbf{i}$ and the actual value $\mathrm{y_i}$. The second component Ω is the penalty for model complexity (e.g. function of a regression tree). The additional normalization components smooth the learned final weights to avoid over-fitting. Visually, the normative objective tends to choose a model that uses simple but highly predictive functions.

The Gradient Tree Boosting algorithm is performed when the model is continuously trained in the way of feature addition. Formally, if $\hat{\mathrm{y}}_\mathrm{i}^{(\mathrm{t})}$ is the i-th prediction value at the $\mathrm{t^{th}}$ loop, the algorithm will need to add the $\mathrm{f_t}$ component to reduce the objective function as follows:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(\mathrm{y}_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (3)$$

The second order approximation is used to optimize faster than the objective function in the algorithm implementation.

$$\mathcal{L}^{(t)} \cong \sum_{i=1}^{n} \left[l\left(\mathrm{y}_i, \hat{y}^{(t-1)} + g_i f_t(x_i)\right) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (4)$$

where $g_i = \partial_{\hat{y}^{(t-1)}} l\left(\mathrm{y}_i, \hat{y}^{(t-1)}\right)$ and $h_i = \partial^2_{\hat{y}^{(t-1)}} l\left(\mathrm{y}_i, \hat{y}^{(t-1)}\right)$ is the first and second order gradients on the loss function. We can remove the constants to obtain a simpler objective function as follows in step t.

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{n} [\mathrm{g}_i f_t(x_i) +] l\left(, \hat{y}_i^{(t-1)} + \frac{1}{2} h_i f_t^2(x_i)\right) + \Omega(f_t) \quad (5)$$

Definition that $I_j = \{i|q(x_i) = j\}$ is the set representing the composition of leaf j. We can calculate the optimal weight w_j^* of leaf j by:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \quad (6)$$

Calculate the corresponding optimal value by:

$$\tilde{\mathcal{L}}^{(t)} = -\frac{1}{2} \sum_{j=1}^{T} \frac{\left(\sum_{i \in I_j} g_i\right)^2}{\sum_{i \in I_j} h_i + \lambda} + \gamma \mathrm{T} \quad (7)$$

Equation (7) can be used as a scoring function to measure the quality of a tree structure q. This score is the same as the classification score for evaluating decision trees, except that it is computed for a wider range of objective functions.

In essence, the XGBoost algorithm uses gradient boosting techniques to identify new trees that are generated on the basis of minimizing the error from the previous tree, adjusting the error weight to get a good tree. Therefore, the faulty points in the previous tree will have a better chance of being corrected in the next tree. The proven XGBoost algorithm optimizes speed and performance for building predictive models. At the same time, the XGBoost algorithm uses a variety of data formats, including tabular data of different sizes and layered data types.

For the comparative models, this study applies the networks VGG16, VGG19, InceptionV3 and ResNet151 with the same image size, no additional image generation, also no fine-tune of parameters and use softmax function to classify weather images. In which, VGG16, VGG19 was born in 2015 and is a CNN network with 16 layers and 19 layers respectively. InceptionV3 was born in 2016, is the 3rd generation of Google's CNN network architecture, with less than 25 million parameters. ResNet 151 belongs to the family of CNN networks of the ResNet (Residual Network) family, born in 2015 with shortcut architecture between hundreds of network layers to contribute to overcoming the phenomenon of vanishing gradients. The general model applied on the matching networks for the weather image classification problem is described in Figure 2.

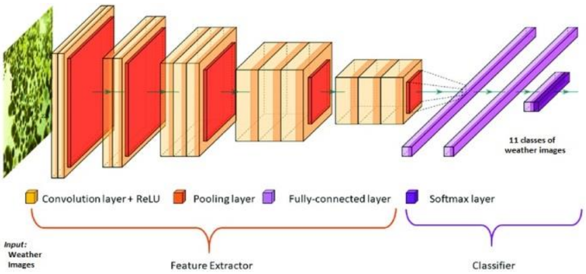

Figure 2: Model of comparative networks

B. Description of dataset for implementation

This study used the WEAPD dataset of 6,862 images [9] collected under various weather patterns (Figure 3) for implementation of proposed model.

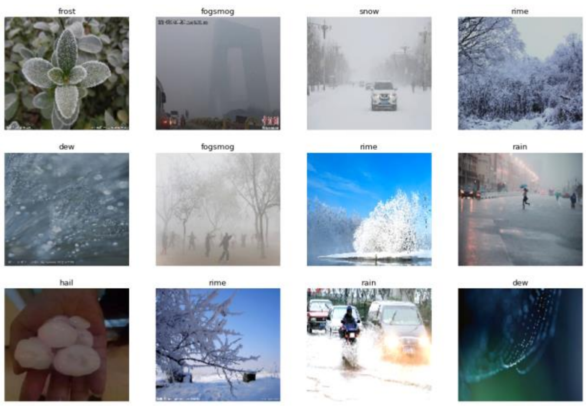

Figure 3: Example of dataset WEAPD

In the WEAPD dataset, the weather images are divided into 11 different image categories (Figure 4). We can see that the dataset is imbalanced (imbalance number of images) between the image data classes. In order to unify the comparison parameters, this study did not duplicate the images through performing under-sampling and over-sampling techniques to obtain balanced dataset. In other words, both the proposed model and the matching model use the original dataset, which is still unbalanced data from the original data.

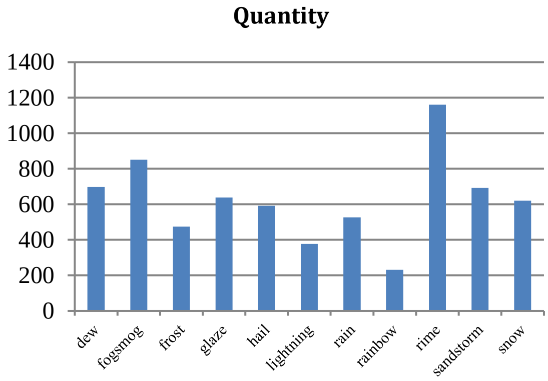

Figure 4: Number of images by labels

IV. EXPERIMENT AND RESULTS

We leave out the fully connected layers of VGG16, keep only the feature extraction and use XGBoost to classify the weather images. There are some hyperparameters of models, such as tree depth max_depth = 3, min_child_weight = 1, n_estimators = 100, and objective using multi:softprob in XGBoost algorithm. The data is divided 80% for the training part, and 20% for the test of the model using the random splitter. The model test results achieved an accuracy of **80.41%.**

The confusion matrix showing correct and mistaken classification between 11 weather data classes of the proposed model is shown in Figure 5 below.

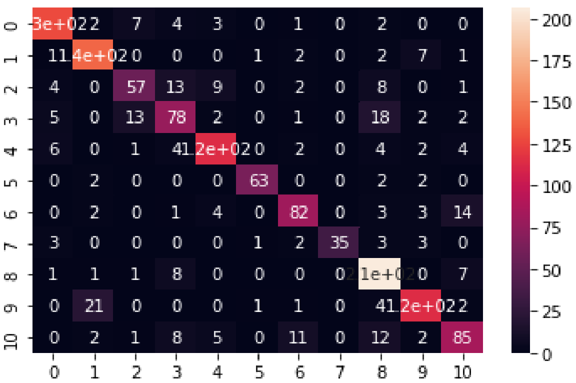

Figure 5: Confusion matrix

For the comparative models, the training process with epochs is 15, the batchsize is 16. The data is divided 80% for the training part and 20% for the test part. Image data remains the same and does not generate image data (no image augmentation), accepting an imbalanced data set (imbalanced dataset). The results of testing the comparative models are shown in Table 1 below.

Table 1: Metric parameters of comparative networks

Classes	**Xception**			**InceptionV3**		
	Pre.	*Recall*	*D1-score*	*Pre.*	*Recall*	*F1 -score*
dew	0.94	0.94	0.94	0.91	0.89	0.90
fogsmog	0.91	0.91	0.91	0.93	0.89	0.91
frost	0.72	0.72	0.72	0.85	0.47	0.61
glaze	0.78	0.78	0.78	0.77	0.82	0.79

hail	0.77	0.77	0.77	0.91	0.81	0.86
lightning	0.77	0.77	0.77	0.74	0.55	0.63
rain	0.67	0.67	0.67	0.72	0.84	0.78
rainbow	0.71	0.71	0.71	0.56	0.80	0.66
rime	0.90	0.90	0.90	0.85	0.94	0.89
sandstorm	0.84	0.84	0.84	0.85	0.83	0.84
snow	0.93	0.93	0.93	0.87	0.88	0.87
accuracy			**0.80**			**0.79**
macro avg	0.81	0.80	0.80	0.81	0.79	0.79
weighted avg	0.81	0.80	0.80	0.81	0.79	0.79
Classes	**VGG19**			**VGG16**		
	Pre.	*Recall*	*F1 - score*	*Pre.*	*Recall*	*F1 -score*
dew	0.71	0.94	0.81	0.84	0.86	0.85
fogsmog	0.69	0.81	0.74	0.88	0.77	0.82
frost	0.63	0.67	0.65	0.75	0.67	0.71
glaze	0.88	0.71	0.79	0.82	0.82	0.82
hail	0.78	0.68	0.73	0.81	0.87	0.84
lightning	0.69	0.52	0.59	0.74	0.64	0.68
rain	0.73	0.81	0.77	0.77	0.81	0.79
rainbow	0.68	0.60	0.64	0.68	0.66	0.67
rime	0.90	0.85	0.88	0.84	0.95	0.89
sandstorm	0.59	0.86	0.70	0.75	0.81	0.78
snow	0.90	0.82	0.86	0.85	0.82	0.84
accuracy			**0.74**			**0.79**
macro avg	0.74	0.75	0.74	0.79	0.79	0.79
weighted avg	0.75	0.74	0.74	0.79	0.79	0.79

Thus, the experimental results on a set of 6,862 WEAPD weather images with 11 different classification labels between the CNN combined model with XGBoost and 4 comparative models (Xception, InceptionV3, VGG19, and VGG16) have shown the measurement among them. The accurate classification of 11 weather image classes is shown in Table 2 below.

Table 2: Comparison of Model Accuracy

Model	*Accuracy*
VGG16-XGBooost	**80,41%**
Xception-Softmax	80,01%
InceptionV3-Softmax	79,23%
VGG19-Softmax	74,51%
VGG16-Softmax	79,12%

The comparison table of classification results compared to other comparative networks shows that the VGG16-XGBoost network achieved the highest accuracy, reaching 80.41% for the classification problem of 11 weather image classes applied to the WEAPD dataset. Thus, the accuracy of the VGG16-XGBoost network model is the best for the classification problem of 11 weather image classes.

V. CONCLUSIONS AND FUTURE RESEARCHES

This study proposed to apply the deep learning CNN model trained by VGG16 to extract image features, combine the XGBoost algorithm to classify images, and apply it to the problem of image recognition and weather assessment. The test results of the VGG16-XGBoost network model achieved the highest accuracy, reaching 80.41% for the classification problem of 11 weather image classes applied to the WEAPD dataset, higher than the test results on some other deep learning networks such as VGG19, VGG16, Xception, InceptionV3. Thus, the research results show that the CNN deep learning network model combined with the XGBoost algorithm is suitable for application in the evaluation of images describing different types of images.

The future direction of further research development can test the application of networks such as Vision Transformer for weather imaging problems or combine deep learning CNN networks with other classifiers according to SVM, Random Forest algorithms... and apply them for image processing problems with different datasets.

REFERENCES

[1] L. Kang, K. Chou and R. Fu, "Deep Learning-Based Weather Image Recognition", 2018 International Symposium on Computer, Consumer and Control (IS3C), 2018, pp. 384-387, doi: 10.1109/IS3C.2018.00103.

[2] Mohammad F. N. and Selvia F. K., "Weather image classification using convolutional neural network with transfer learning", AIP Conference Proceedings 2470, 050004 (2022); https://doi.org/10.1063/5.0080195 Published Online: 25 April 2022.

[3] Haixia X., Feng Z., Zhongping S., Kun W., Jinglin Z. (2021) "Classification of Weather Phenomenon From Images by Using Deep Convolutional Neural Network", Earth and Space Science, https://doi.org/10.1029/2020EA001604

[4] Mohamed R. I., James H. and Tao C. (2019) "WeatherNet: Recognising Weather and Visual Conditions from Street-Level Images Using Deep Residual Learning", International Journal of Geo-Information, ISPRS Int. J. Geo-Inf. 2019, 8, 549; doi:10.3390/ijgi8120549

[5] Elhoseiny M., Huang S. and Elgammal A. (2015) "Weather classification with deep convolutional neural networks", Conference: International Conference on Image Processing, doi 10.1109/ICIP.2015.7351424

[6] Manthan Patel, Sunav Das, Dr. N. Krishnaraj (2021) "Weather Image Classification Using Convolution Neural Network", Annals of the Romanian Society for Cell Biology, pp. 4156–4166. Available at: https://www.annalsofrscb.ro/index.php /journal/article/view/2965 (Accessed: 27April2022).

[7] Qasem A. A., Mahmoud A. S., and Saleh Z. S. (2020) "Multi-Class Weather Classification Using ResNet-18 CNN for Autonomous IoT and CPS Applications", 2020 International Conference on Computational Science and Computational Intelligence (CSCI), 2020 IEEE DOI 10.1109/CSCI51800 .2020.00293

[8] Huang G., Liu Z., Van Der Maaten L., and Weinberger K. Q. (2018) "Densely Connected Convolutional Networks", Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, vol. 2017-January, pp. 2261–2269, Aug. 2016, Accessed: May 27, 2021. [Online]. Available: http://arxiv.org /abs/1608.06993.

[9] WEAPD, @data{DVN/M8JQCR_2021, author = {Xiao, Haixia}, publisher = {Harvard Dataverse}, title = {{Weather phenomenon database (WEAPD)}}, year = {2021}, version = {V1}, doi = {10.7910/DVN/M8JQCR}, url = {https://doi.org /10.7910/DVN/M8JQCR} }

[10] Chen and Guestrin (2016) "XGBoost: A Scalable Tree Boosting System", KDD'16: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, August 2016, Pages 785–794, https://doi.org/10.1145 /2939672.2939785.

NHẬN DẠNG HÌNH ẢNH THỜI TIẾT DỰA TRÊN KẾT HỢP CNN VÀ XGBOOST

Tóm tắt: *Nghiên cứu này đề xuất thử nghiệm mô hình kết hợp giữa mạng CNN và thuật toán XGBoost cho bài toán nhận dạng ảnh thời tiết. Mô hình đề xuất sử dụng mạng học sâu CNN cho phần trích chọn đặc trưng, sau đó đưa các đặc trưng vào bộ phân loại XGBoost để nhận dạng các bức ảnh. Mô hình áp dụng tập dữ liệu thử nghiệm là tập 11 lớp ảnh khác nhau thu thập dưới nhiều hình thái thời tiết khác nhau. Cùng tập dữ liệu cũng được thử nghiệm với các mạng học sâu khác gồm Xception, InceptionV3, VGG19, VGG16 theo nguyên tắc chung các tham số, giữ nguyên bản ảnh gốc để so sánh. Kết quả thử nghiệm cho thấy mô hình CNN-XGBoost cho kết quả độ chính xác tốt nhất, phù hợp để ứng dụng trong đánh giá, phân loại các bức ảnh mô tả các loại hình thời tiết khác nhau.*

Từ khóa: *CNN, XGBoost, ảnh, thời tiết.*

Tran Quy Nam graduated as an Engineer degree (in 1999) and got a Master degree (in 2005) in Information Technology from Hanoi University of Science and Technology, and received a PhD in Information Technology Management from Seoul National University, South Korea in 2010. His current research fields are: machine learning, application of artificial intelligence, e-government architecture, digital transformation, information system optimization, multimedia application development.

Vu Huu Tien graduated with undergraduate and graduate degrees in Electronics and Telecommunications in 2002 and in 2004 respectively at Hanoi University of Science and Technology. In 2010, he received his PhD from Chulalongkorn University (Thailand) in Electronics and Telecommunications. He is currently working at the Faculty of Multimedia, Posts and Telecommunications Institute of Technology. His current research fields are: Signal processing and multimedia communication, Multimedia application development.