A 3D Convolutional Neural Network for Anomalous Propagation Identification

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***Abstract*—Radar is one of the most popular and widely used weather observation devices because of its better performance compared to other remote sensing devices. However, the observation results of the radar unavoidably contain unwanted signals, called non-precipitation echoes, which include anomalous propagation. These represent a negative influence, especially in the quantitative precipitation estimation. Therefore, it is essential to remove the anomalous propagation in the radar data for accurate weather forecasting. In this paper, we implemented a three-dimensional convolutional neural network for classifying the anomalous propagation in the radar data. Without considering feature engineering, which is difficult and mostly handcrafted, we were able to obtain improved performance in the classification with actual occurrence cases of the echo.**

Keywords–Pattern recognition; Deep learning; 3D convolutional neural network; Anomalous propagation; Radar data analysis.

I. Introduction

Machine learning, which allows solving real-world problems by utilizing given data, applies to lots of practical fields including medicine [1], finance [2], genetics and genomics [3], etc. Additionally, deep learning [4], a sub-class of the machine learning, significantly influences many aspects of modern society by achieving outstanding improvements especially in large-scale image processing and speech recognition. One of the compelling advantages of deep learning is that it can derive remarkably successful results without considering feature selection [5] and extraction [6]. Therefore, there are a lot of ongoing active studies that aim to lower the expensive computational costs.

These research works influence many academic and practical fields including weather prediction because the weather prediction is intimately connected with modern society [7]. For example, it is possible to protect lives and properties by forecasting storms and local torrential rainfalls. Also, these works help minimize economic damages from agflation caused by abnormal climate changes. Deep learning related studies have been gradually growing to respond to an increased demand for accurately analyzed results from observation devices such as radar and satellite.

Currently published researches related to weather prediction are mainly focused on precipitation nowcasting [8][9] and storm identification [10][11] based on accurately analyzed results of radar observations. The radar is the most popular weather observation device because it can generate spatiotemporal observation results with high resolution, and is able to provide three-dimensional precipitation information in a more direct way than other sensing devices. However, the radar observes all objects in the atmosphere without exception. In other words, the observation results inevitably contain unwanted signals, called non-precipitation echoes.

Non-precipitation echoes have many different causes. The typical non-precipitation echoes are as follows. First, interference [12] occurs by strong wireless impulse signals which have similar bandwidth to radars. Second, biological echo can appear [13] by a flock of birds or insects. Third, ground echo [14] and sea clutter [15] can be present in the radar image by artificial or natural objects on the surface of the earth and the sea. Fourth, chaff echo [16] occurs by scattered lightweight materials from an aircraft or battleship to avoid radar detection. Fifth, anomalous propagation [17] appears by refracted radar beam due to rapid changes in temperature or humidity. Among them, the anomalous propagation causes significant errors in radar rainfall estimation because it is less predictable and has changeable intensity of reflectivity or extension of areas.

In early days, a manual quality control process based on experts knowledge was used to eliminate anomalous propagation. After that, statistical-based [18] and machine learning-based [19] methods were complementary used. However, earlier studies applied conventional machine learning methods which included feature engineering. Considering that feature engineering negatively influences performance, many difficulties followed, unavoidably. In this paper, we implement a non-precipitation echo detection method based on a three-dimensional convolutional neural network. By using our deep learning architecture, it is unnecessary to go through additional feature selection and extraction.

This paper is organized as follows. In Section 2, we briefly present a background knowledge of radar operating principles and anomalous propagation. Section 3 explains convolutional neural network and introduces our 3D architecture. In Section 4, our experimental framework and results are described. Section 5 provides the conclusion and future works.

II. Background

This section explains the operating principle of radar and occurrence properties of the anomalous propagation echo for providing background knowledge.

A. Weather Radar

The primary operating principles of radar are radiating intense electromagnetic energy and gathering backscattered signals from floating objects in the observation hemisphere. In other words, by using electromagnetic energy as its measuring tools, radar computes valuable information for analyzing properties of the reflected signals including distance, power density, radial velocity, etc. [20].

The operating principle makes the radar one of the most popular measurement devices for weather forecasting because the electromagnetic waves travel their pre-set route from the transmitter of radar regardless of weather condition. In other words, radar can operate 24 hours a day, seven days a week in all weather conditions including severely low visibility conditions including fog, rain, snow, and hail.

There are two main types of scans: Range Height Indicator (RHI) and Plan Position Indicator (PPI). The RHI scan provides the image from the side. Lots of studies utilize the RHI scan when an improved vertical resolution is required. On the other hands, the PPI scan produces the image as seen from above [21]. The PPI scan is generally utilized in weather forecasting process because it facilitates to understand time series changes of radar echoes.

B. Anomalous Propagation

The electromagnetic waves follow the quasi-optical laws because they behave similarly to light beams in a uniform and constant medium. But the precondition is rarely satisfied in the earth's atmosphere in practice. In other words, the refraction of the emitted electromagnetic waves is a common phenomenon because of several factors including pressure, temperature, and vapor pressure. Considering that the primary operating principle of the radar is based on the condition that the emitted electromagnetic waves travel in an ideal atmospheric environment, measurement results are inevitably wrong. Therefore, standard refraction based on these factors is commonly used in actual observation instead of no refraction condition.

From a different point of view, the radiated electromagnetic waves from the radar can travel in various directions due to refraction when the specific conditions are satisfied. For instance, the rapid changes of a temperature gradient, pressure or water vapor content can bend the waves or even trap them in a specific layer in the air. As a result, when the rapid changes of the atmospheric condition refract the radar beam, there is a chance that the radar cannot perceive the difference which can derive significant wrong results in weather forecasting.

There are two typical different cases of the refracted pathways: the radar shows nothing when raining, and the radar shows precipitation echoes without raining. The former situation occurs when the radar beams are refracted toward the opposite direction of the surface, which is called sub-refraction. And the latter situation occurs when the radar beams are refracted toward the surface, which is called super-refraction. In this case, the radar misrecognizes the objects on the earth or sea surface as precipitation echoes. The misrecognized echo is called anomalous propagation.

Notably, the anomalous propagation causes significant errors in radar rainfall estimation because it is less predictable and it has the changeable intensity of reflectivity or extension of areas. Therefore, the anomalous propagation should be removed from the radar observation result for accurate weather forecasting. Figure 1 and Figure 2 show individual cases of precipitation and anomalous propagation, respectively. As

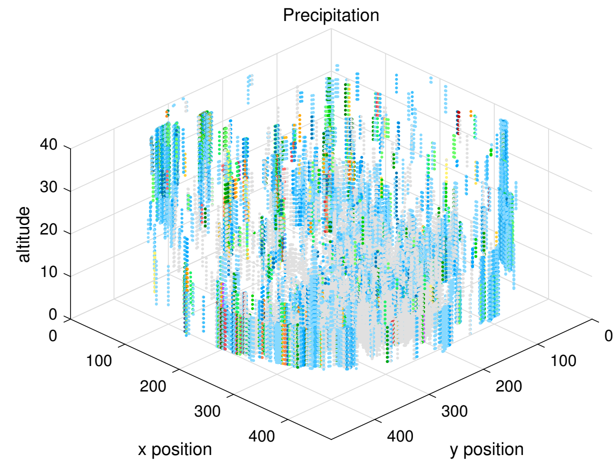

Figure 1. Precipitation case

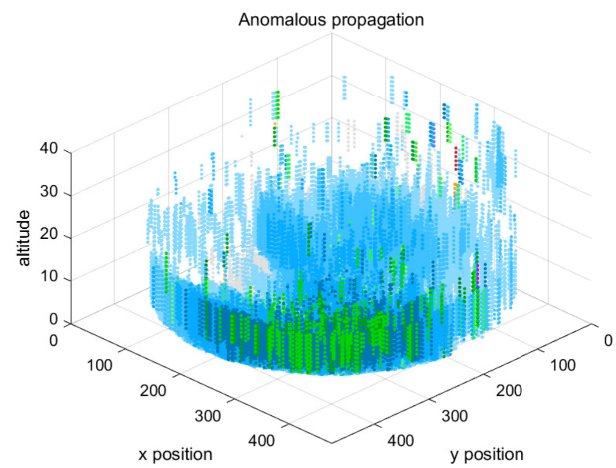

Figure 2. Anomalous propagation case

shown in the figures, it is difficult to distinguish which one is precipitation and which is anomalous propagation without a quality control process.

III. METHODS

This section provides brief elucidations about a conventional artificial neural network, a convolutional neural network that is one of the outstanding deep learning models, and detailed explanations about our implemented three-dimensional convolutional neural network.

A. Artificial Neural Network

The artificial neural network is a mathematical algorithm for high-level data processing which is inspired by biological nerve systems. It is confirmed that the biological nerve system is a source of the artificial neural network because the operating principles of their basic components are considerably similar. Many practical applications frequently use the artificial neural network for solving their problems because the

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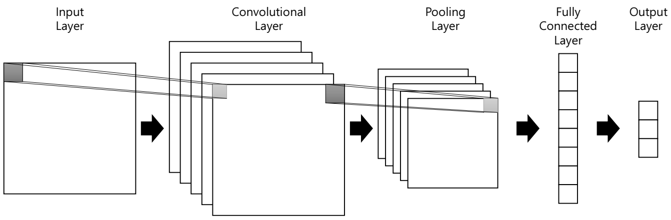
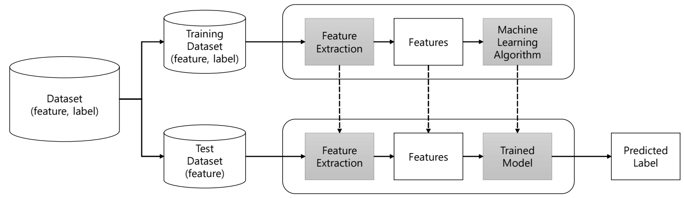
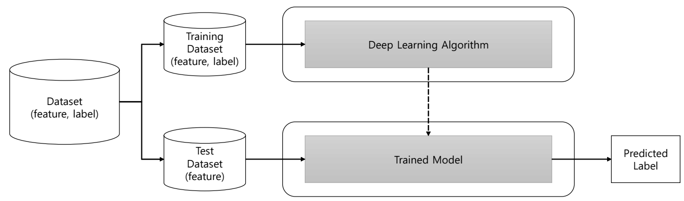


Figure 3. Simplified convolutional neural network



(a) Conventional machine learning



(b) Deep learning

Figure 4. Comparison of model learning process

model has good performance in classification, regression, and clustering [22].

Layers are typical organizations of the artificial neural network. Nodes, which contain an activation function, are components of the layers. The artificial neural network can solve difficult problems by using highly interconnected and weighted nodes. There are three types of layers: input, hidden, and output. When the artificial neural network gets a multidimensional vector as an input, the input layer distributes the input to the hidden layer. And the hidden layer determines whether the outputs of the previous layer are helpful or harmful to the final result and distributes its output by using weighted sum and activation function. The output layer finalizes outputs of the previous layer. In summary, it is possible to describe the operating principle of the artificial neural network in (1).

$$y = f_h\left(\sum_{i=1}^{n} \omega_i x_i - b\right) \tag{1}$$

where $f(\cdot)$ is an activation function, n is the number of variables x_i from the previous layer, ω is weights, and b is biases.

However, despite the outstanding performances of the conventional artificial neural network in various practical fields, the requirement of significant computational complexity is the most substantial limitation of the model when it needs to deal with image processing. For example, the conventional model requires $12,228$ weights in the first hidden layer for analyzing a 64×64 color image. Additionally, considering that the network structure should be a lot larger than the input image, the conventional neural network seems not manageable for the given problem. In other words, there are two main reasons why the conventional neural network is not suitable for image processing. First, it is necessary to provide unlimited computational power and time for training the huge model. Second, it might cause over-fitting problem.

B. Convolutional Neural Network

For solving the two problems of the conventional model, a convolutional neural network is suggested [23]. The convolutional neural network has similar components to the conventional artificial neural network. Namely, they have identical structures, components, and backpropagation based on the self-optimisation process. But a noticeable difference exists between the conventional neural network and the convolutional neural network in that the latter has three salient types of layers: convolutional, pooling and fully-connected layers. Figure 3 illustrates the simplified example of the convolutional neural network.

When the input layer distributes the pixels of the image as inputs, the convolution layer convolves each filter across the data to produce a two-dimensional activation map. By using a zero-padding process, it is possible to keep the size of each convolved data as given inputs. The pooling layer reduces the data from the convolution layer with activation function for curtailing the number of parameters and the computational complexity of the model. The fully-connected layer performs the same roles as the conventional neural network and attempts to derive scores from the activation functions. Finally, the convolutional neural network uses the derived scores for classification.

Furthermore, there is another advantage to notice in the convolutional neural network that the convolution layers in the model can extract features from given input data. In the majority of conventional machine learning algorithms, they should include feature engineering in a training phase. The principal point is that most of the features are hand-crafted, which is difficult, time-consuming and requiring domain expertise. Also, if the extracted features could not describe the given data well, it is possible to degenerate performances of the model. Figure 4a shows the learning and prediction phases of the conventional machine learning methods, which include the feature extraction in the process. On the other hand, it is unnecessary to put the time and effort into feature engineering when the convolutional neural network is applied. Figure 4b illustrates the learning and prediction phases of the deep learning including the convolutional neural network. It is easily noticeable in Figure 4 that the feature extraction process is not necessary for the deep learning implementation.

C. 3D Convolutional Neural Network

In this paper, we implemented a three-dimensional convolutional neural network for practical utilization in radar data analysis. The architecture of the model is shown in Figure 5, which contains four hidden convolution layers and a fully-connected layer. The convolution layers contain convolution filter, ReLu activation function $(f(x) = max(x, 0))$, and max-pooling. Additionally, dropout is applied for preventing overfitting.

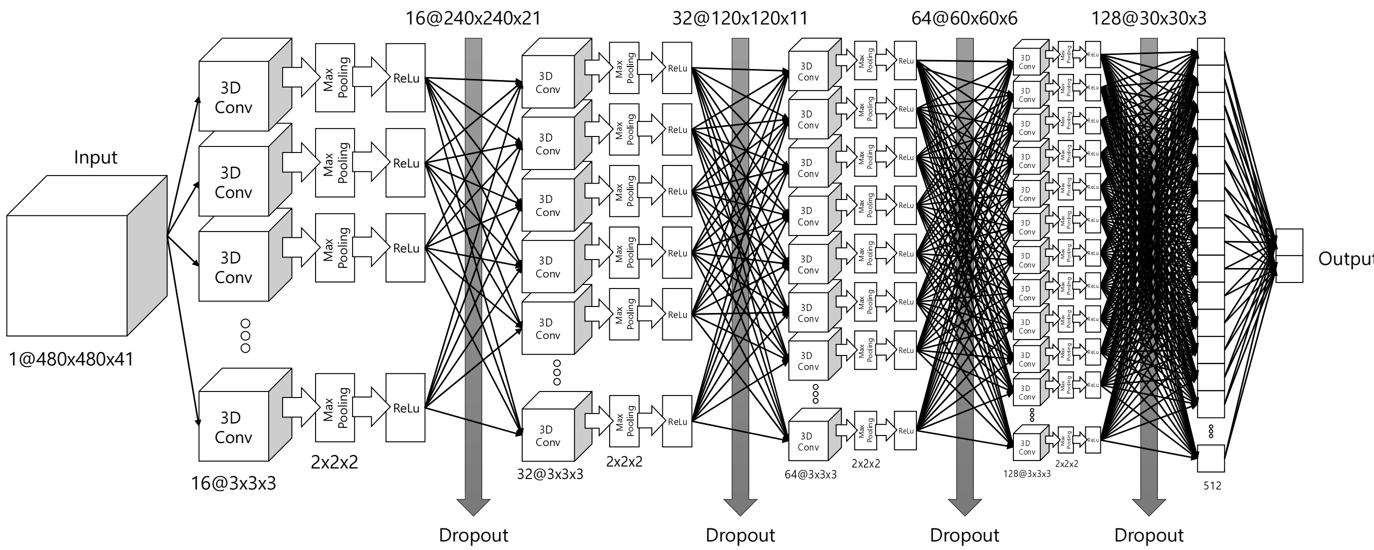


Figure 5. 3D Convolutional neural network structure

The implemented three-dimensional convolutional neural network is similar to the architecture of two-dimensional convolutional neural networks. But, unlike the bidimensional convolutional neural network structure, the implemented model utilizes tridimensional convolutional filters, activation functions, and max-poolings. We chose a $3 \times 3 \times 3$ size structure for convolutional filters by conducting empirical experimentations. Also, we designed the convolution layers so that the shape of input and output is identical by using a zero-padding process. In case of max-pooling, we chose a $2 \times 2 \times 2$ shape. This kind of max-pooling structure allows reducing the computational complexity of the convolutional network for both two- and three-dimensional structure. Similarity and dissimilarity of the convolutional neural network structures are easily found in (2) and (3).

$$v_{ij}^{xyz} = f\left(\sum_{m}\sum_{p=0}^{P_i-1}\sum_{q=0}^{Q_i-1}\omega_{ijm}^{pq} v_{(i-1)m}^{(x+p)(y+q)} + b_{ij}\right) \quad (2)$$

$$v_{ij}^{xyz} = f\left(\sum_{m}\sum_{p=0}^{P_i-1}\sum_{q=0}^{Q_i-1}\sum_{r=0}^{R_i-1}\omega_{ijm}^{pqr} v_{(i-1)m}^{(x+p)(y+q)(z+r)} + b_{ij}\right) \quad (3)$$

where (x, y, z) is a coordinate of feature map and volume, (p, q, r) is a spatial dimension index of kernel, i indicates convolution layer, b_{ij} means bias, and $f(\cdot)$ is an activation function.

Also, for applying the rule [24], we tried to add more layers in the architecture. As a result, we implemented another convolutional neural network, which additionally contains a fully-connected layers, as shown in Figure 6. As for the same structure described in Figure 5, the convolution layers contain a convolution filter, ReLu activation function, max-pooling and dropout. The difference between the two models is illustrated in Table I for readibility.

IV. Experiments

Currently, the implemented network is designed as a binary classification as shown in Figure 5 because it is hard to obtain the sufficient number of individual recurrence case of each non-precipitation echo. Also, the simultaneous occurrence cases of the non-precipitation echoes are more frequent than the standalone occurrence cases. Therefore, we utilised learning of the implemented model by using two days of anomalous propagation and two days of precipitation. And we applied the other data for testing which contains both precipitation and anomalous propagation separately. In summary, we used 508 numbers of tridimensional radar images as training data and 144 number of radar images as test data. Also, we trained the implemented models with the Adam optimizer at a learning rate of 0.001.

The testbed environment configuration was as follows:

- CPU: Intel i7-7700K @ 4.20GHz $\times$ 8
- RAM: 16GB DDR4
- GPU: NVIDIA GeForce GTX1080/PCIe/SSE2
- Framework: TensorFlow 1.4.1, Python 3.5.2
- OS: Ubuntu 16.04 LTS

For evaluating the implemented three-dimensional convolutional neural network, we conducted evaluations using accuracy as shown in (4).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

where TP indicates true positive, TN indicates true negative, FP indicates false positive, and FN indicates false negative. Also, we utilised the terms that true indicates the anomalous propagation echo, and that false indicates the non-anomalous propagation echo, respectively.

We derived the results from the implemented models in Figure 5 and Figure 6. By using the model in Figure 5, it showed classification accuracy as 68.75% on average. On the

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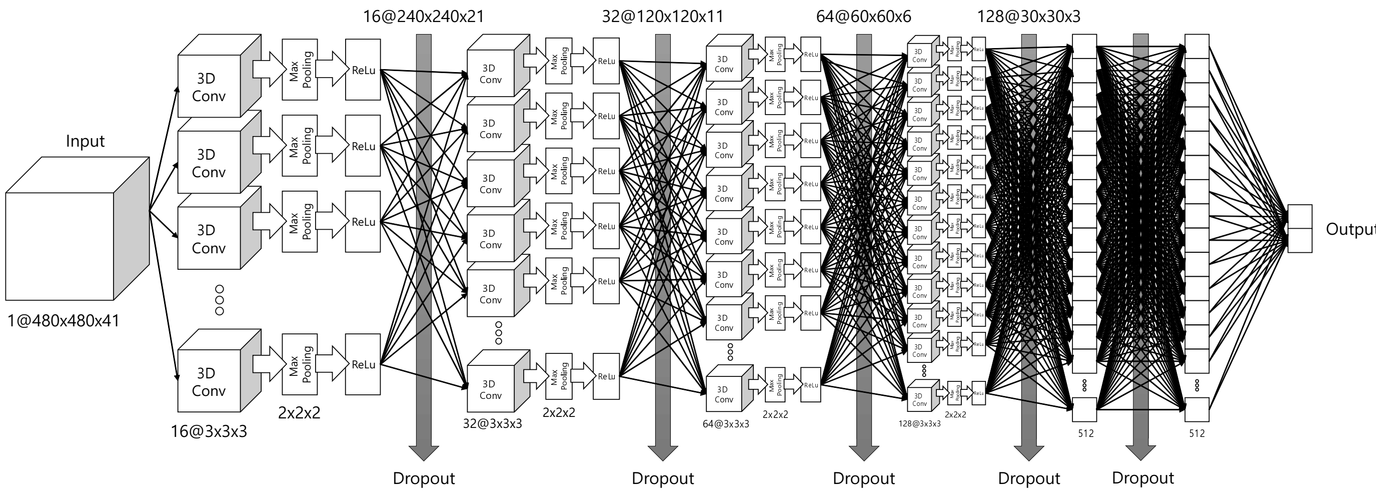

Figure 6. Extended 3D Convolutional neural network structure

TABLE I. THREE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORKS FOR EXPERIMENTATION

	Configuration											
3DCNN	input	16@conv3d	maxpool	32@conv3d	maxpool	64@conv3d	maxpool	128@conv3d	maxpool	FC-512	softmax	
3DCNN_Extended	input	16@conv3d	maxpool	32@conv3d	maxpool	64@conv3d	maxpool	128@conv3d	maxpool	FC-512	FC-512	softmax

other hands, by using the model in Figure 6, it showed better average accuracy as 72.22%. From the experimental results, we can conclude that the three-dimensional convolutional neural network as shown in Figure 6 shows better results because the two sequentially connected fully-connected layers operate as the conventional neural network.

V. Conclusion and Future Works

In this paper, we implemented a three-dimensional convolutional neural network for classifying the anomalous propagation in the radar data as a feasibility study. The implemented model was able to learn volumetric features in tridimensional radar data without information loss. As a result, the three-dimensional convolutional neural network was able to identify the anomalous propagation by using actual occurrence cases of the anomalous propagation.

In future works, we will try to implement multi-class classification method by using the proposed method as a prototype. Currently, the implemented network is designed as a binary classification to classify the whether the given tridimensional is an anomalous propagation or not. The convolutional neural network is easy to expand from binary to multi-class classification by expanding the number of layer elements of the output layer. Additionally, the multi-class classification based approach is a more beneficial way to utilize in practical fields because it is more prone to occur different types of non-precipitation echoes simultaneously.

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