International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Framework for Flood Extent Mapping using CNN Transfer Learning

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Submitted: 19/09/2022 **Accepted:** 26/12/2022

Abstract: One of the most common natural disasters is flooding that endangers infrastructure and life of human beings, particularly in heavily populated areas. The ability to identify flooded regions quickly and precisely is critical for emergency response planning and damage assessment. This research is aimed at mapping the flooded regions as per their severity levels to improve community resilience and decision making in disaster scenarios. To accomplish this task, image classification technique is used. In this study, for the purpose of classification our designed dataset having images of the flood of varying severity levels are categorized into three classes viz mild, moderate, and severe. Further to improve the classification task, Convolutional Neural Networks (CNNs) with transfer learning approach is used. CNN is powerful enough to extract features from large volumes of visual data and is particularly excellent at exploiting semantic information, however, requires huge amount of training data. In this article instead of building and training a CNN from start for flood severity image classification, pre-built and pre-trained networks via transfer learning are used. A comparative analysis using VGG16, MobilNet, and ResNet50 (which are prominent CNN pretrained models) has been performed in this study. The average recall, precision, and F1-score are used to assess performance. Experiment analysis shows that fine-tuned pretrained ResNet50 model performs better as compared to state of art models for flood image classification application.

Keywords: *Image classification**,** Convolutional Neural Networks, Flood severity classification, Transfer learning, pre-trained models.*

1. Introduction

Every year, flooding causes tens of thousands of fatalities. In the past years, many violent calamities have occurred. Natural catastrophes and their consequences have been documented in history since 1500 BC. The globe has been driven towards tumultuous manufactured calamities by an uncontrollable population and pressed urbanisation [1]. Despite technological advancements and extensive study into weather forecasting systems, human being is unable to prevent calamities from occurring. Nature is always the greatest power. Floods, droughts, flash floods, cloud bursts, cyclones, and earthquakes have become recurrent natural catastrophes in India in recent years, owing to global warming. Extreme weather, climate change, and uncontrolled urbanisation are all common causes of flooding. Heavy rainfall, cyclonic storms, and thunderstorms are examples of meteorological factors that might induce it. Coastal city drainage is hampered by hydrological factors such as overbank channel networks and high tides occurrence. Low-lying regions are the major pockets that flood every monsoon because storm water drains are found to be insufficient to convey the surface runoff due to fast growth in the built-up area and a lack of structural design of water drains. The major cause of urban flood is urbanisation, which increases the surface resistance. In numerous ways, haphazard building activities in metropolitan areas have a negative influence on natural drainage systems [2].

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Every year, natural calamities such as flood hit very badly in India. Environmental deterioration, such as deforestation, intensive land usage, and rising population appear to have increased the effect and probability of occurrence in recent years [3]. In respect of human social and economic loss, floods are the most common and costly natural catastrophes. Damage of 75-80% has accounted due to flooding caused by natural catastrophes in India. As per the UN Office for Disaster Risk Reduction's Global Assessment Report 2017, average yearly flood event damage in India is as high as 7472 million US dollars.

Many organisations (e.g., management agencies, lawmakers, and local administration officials) require proper early warning and preparedness systems and technologies in place to limit the destructive impacts of extreme weather occurrences. For flood emergency response, mapping flooded regions during and shortly after flooding is vital. Flood hazard forecasting can save human lives and reduce infrastructure damage by giving quick damage estimates and allowing relief efforts to be planned more efficiently.

For urgent emergency reaction, accurate and timely retrieval of the flood depth is critical. To identify the flooded regions, several image classification approaches such as Support Vector Machines (SVMs) have been applied [4]. SVMs work effectively for remote sensing applications that require a small quantity of data but, as the amount of training data grows, the complexity increases. For image classification, object identification, and recognition tasks, deep learning techniques such as Convolutional Neural Networks (CNN) [5] and Recurrent Neural Networks (RNN) [6] have been used in recent years. Because of its capacity to effectively handle huge training data sets, CNNs are commonly employed in image classification [7,8]. They generally achieve greater classification accuracy than older approaches. Through the structure of multi-layers of neurons, CNNs can learn features automatically from enormous datasets [9] and can apply nonlinear decision functions [10].

2. Related Work

Unlike physical models, the ANN model is data-driven and does not require any spatial based parameter. A precipitation-runoff model, for example, should be evaluated using several factors based on complicated geological parameters with physical laws in the target watershed [4]. The setup of a physical model, like the precipitation -runoff framework, takes a lot of time and effort. The ANN model may forecast a near-future trend based solely on prior data learning. Although ANN prediction has a low computing cost, learning has a significant computational cost. The ANN-based flood model's main advantages include a speedy response to indications to forecast flood event and a simple to run utilising just past data [11].

ANN models have been used to predict floods in several studies [12]. Practical flood forecasts have recently been made using ANN models that use machine learning and deep learning approach [13]. The long short-term memory (LSTM) framework [14,15] was used as another form of ANN model for water-level forecasts during flood occurrences.

With many datasets, ANN models correctly predicted prior flood occurrences in most case studies. Because of the big datasets, ANN models in general have substantial computing costs throughout the training phase. This work uses a transfer-learning strategy to lower the huge costs of computing runs [16]. The approach is based on the concept that a model that has been pre-trained on huge datasets in one domain may be employed in other target areas. The retrained model can deliver acceptable outputs at a minimal computational expense.

Through enhance classification accuracy, image classification research has seen the advancement of algorithms from first order moments to deep learning techniques. First order moments and grey level dependence characteristics were used to derive textural information for this development [17]. For texture categorization, they developed grey level dependency statistics. In addition, to integrate metadata in texture classification, a structural method for has been developed [18]. For content-based image retrieval an application of image processing, first order moments were employed to extract texture features from the input images [19]. First order moments, on the other hand, are neither scale nor rotation invariant. Gabor filters were introduced with application to texture classification to overcome invariance problem [20]. In addition, for texture categorization, supervised learning [21] was used.

Deep learning is the newest artificial intelligence trend. Though the theoretical principles underlie deep learning are just not recent, the field has seen a boom in recent years. Deep learning algorithms, have beaten various tasks, including image processing, audio and video processing, and Natural Language Processing (NLP) [22]. Some researchers have worked on designing better optimizers to cope with the difficulty of training deep networks. For training moderately deep networks, well-designed hyper parameters are used [23].

Different deep learning networks such as maxout and DasNet are trained to learn precise internal attention to certain attributes extracted from images, DNGO allows effective optimization of noisy functions. Drop-Activation and a regularisation strategy are used for randomness on the activation function, increases generalisation in most current neural networks [24].

Many researchers have explored above mentioned deep learning models with CNN for applications such as Fauna Image Classification [25], Fundus Image Classification [26], Hyperspectral Imagery (HSI) classification [27] and many more such applications recently. Experiments are also conducted to verify and prove that CNN-Softmax performs well compared to CNN-SVM on most datasets [28].

A major stumbling point in CNN training is the lack of a large-scale database. A CNN framework with a multiple layer design with many inputs has better classification performance, but the model becomes too complex and takes a prolonged time to infer. The use of a pretrained network creates a group of common feature map and finetunes the network for a particular task is a key approach in the application of image classification. It does, however, have two significant shortcomings: First, the pretrained networks tend to overfit on some data sets since these networks contain huge dimensions that are manually designed to collect enough representation on huge data sets. Second, classification algorithms are often used in resource-constrained applications, such as embedded aerial SAR data processing, where storage, computing, and power are restricted. Some applications, such as surface object identification in a military environment and land categorization of seismic hazard information from SAR data, need low-latency analysis. Deep and massive pretrained networks, on the other hand, have high reasoning and storage costs, making them challenging to use in the above cases. To address these issues, several researchers used the CNN model compression approach to compress the classification model and achieved satisfactory results. [29].

3. Theoretical Background of the Employed Algorithms

The proposed methodology uses CNN with transfer learning. The following are the theoretical background in these two fields.

3.1 Convolutional Neural Network (CNN)

Deep leaning networks, such as CNNs, have the following benefits over the other structural models: (a) To retrieve abstract data features, CNNs perform a convolution operation on the pixel values of an image. This feature extraction is stronger in terms of generality and may be used in a variety of contexts. The detailed architecture is shown in figure 1. (2) CNNs can represent image data in a distributed fashion and collect feature data quickly from large amounts of data. CNNs have a framework that allows them to solve difficult nonlinear problems successfully. (3) CNNs include sparse connections, weight-sharing, and spatial subsampling, that results in a more flexible network structure.

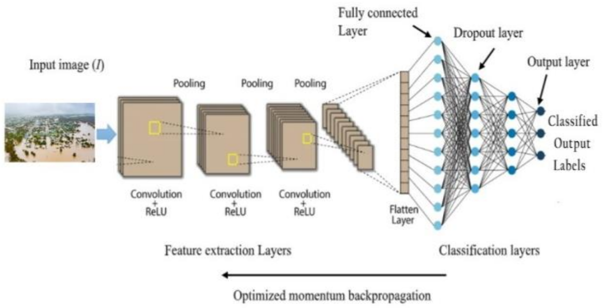

Fig. 1 Architecture of Convolutional neural network for image classification

Despite the benefits of CNN outlined above, adequate training data is required to train CNN models for image categorization. Data augmentation approaches for dealing with limited training data are the subject of certain investigations. The training data size and diversity are augmented using data augmentation approaches. However, when used to train sophisticated or massive deep learning models, they are insufficient. For specialised applications like remote sensing, a huge increase in training datasets in image categorization is critical.

The majority of CNN-based image classification research place a greater emphasis on classification accuracy. Only a few research have looked at how efficient a CNN is at training CNN models. High-end computing hardware (e.g., GPUs) can be utilised to speed up the model training and testing to fulfil the criteria of big data images in practical production. Transfer learning, a deep learning technique in which a network generated for one job is reused as the starting point for a second task, is a very effective strategy to speed up training time and accuracy when there is a scarcity of training data to solve the challenges listed above [30].

3.2 Transfer Learning

Tasks like image categorization cannot attain human-level performance before deep learning takes off. This is due to the fact that a machine learning model cannot learn an image's neighbour information. The model can only receive pixel-level data. Machine learning models also have a major drawback is that they need a significant volume of data to develop. Using the CNN model, image classification has attained a high degree of performance. However deep learning models like CNN are capable achieving human-level performance, needs a significant quantity of data. If we don't have them, researchers can make use of a technique known as transfer learning. A saved model that has been trained previously on a large dataset, usually on a large-scale image-classification job, is well-known as a pre-trained model. Use the pretrained network as is or use transfer learning approach to fine tune to a specific job. Transfer learning strategy for classification task is based on the idea that if a model is trained on a large volume dataset, it may successfully serve as a basic model of the diverse image. The learnt feature maps may then be used by everyone without having to start the training from the beginning on a large dataset. The architecture of transfer learning is depicted in figure 2.

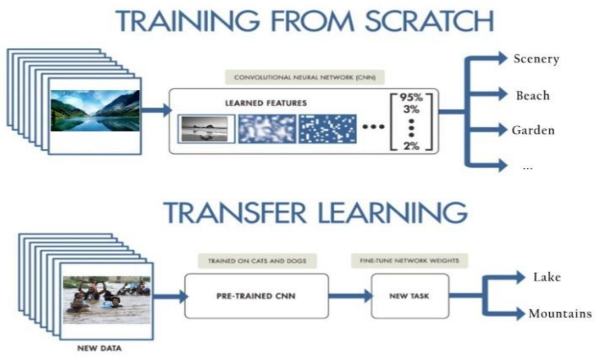

Fig. 2 Architecture of Transfer Learning for Image Classification

The most prominently used pretrained networks are VGG Net, ResNet, DenseNet, Inception Net, Xception Net and MobileNet. In the next section different pretrained networks are discussed which are used in our experimentation.

3.2.1 VGG Net: Among all CNN architectures, VGG Net is the most straightforward network. Even though it appears to be simple, it outperforms several more complicated structures. There are six VGGNet architectures in all. VGG-16 and VGG-19 are two of the most popular. The architecture of VGG 16 is as shown in figure 3. The convolutional layers of the VGG architecture are layered with progressive kernel sizes. If layer 1 contains 16 filters, layer 2 must have at least 16 filters. Another interesting feature is that all filters in every VGG design are 3*3 in size. The concept is that two 3*3 filters virtually cover the same area as one 5*5 filter, and that two 3*3 filters are less computationally expensive than one 5*5 filter.

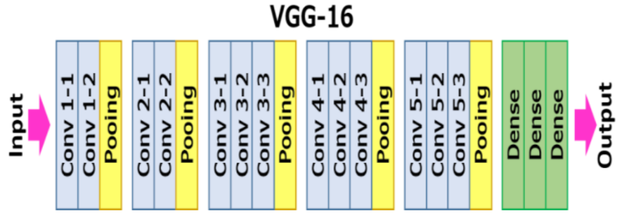

Fig. 3. VGG16 model architecture [32].

3.2.2 ResNet: ImageNet's initial ResNet, which was used in 2015, comprises 152 layers. ResNet's ability to train such a deep (152 layer) network is due to its residual connections. Every layer of VGG is linked to the preceding layer, from which it receives its inputs. This ensures that when layers are propagated, more and more valuable features are carried over while less significant ones are eliminated. This is not the ideal method because the subsequent layers cannot see what the previous levels have seen. ResNet solves this problem by linking both the prior and current layers, as well as a layer beneath the previous layer. As a result of this, each layer may now see much more than just its own [34]. Detailed framework of residual learning block and ResNet architecture is as shown in figure 4.

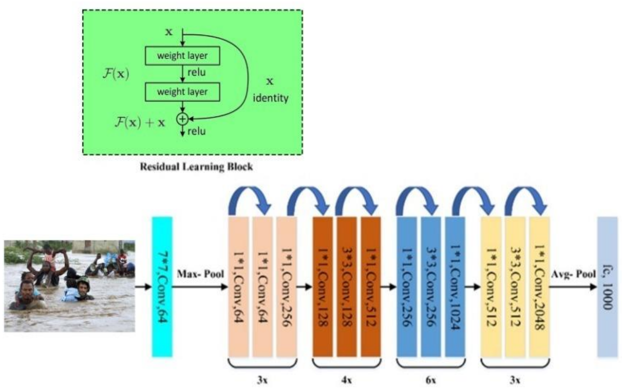

Fig. 4. The architecture of ResNet-50 model.

3.2.3 MobileNet: Instead of standard convolutions, this design uses Depth wise Separable Convolutions. As a result, it's better suited to low-power gadgets and models with rapid reactions. When compared CNN of the same depth, it dramatically reduces the number of parameters which results in lightweight deep neural networks. The key difference between MobileNet and typical CNN architecture is that convolution was broken into two parts by Mobile Nets: a 3x3 depth-wise convolution and a 1x1 pointwise convolution as shown in figure 5. These are created to enhance accuracy while keeping in mind the limited resources available for an on-device or embedded application.

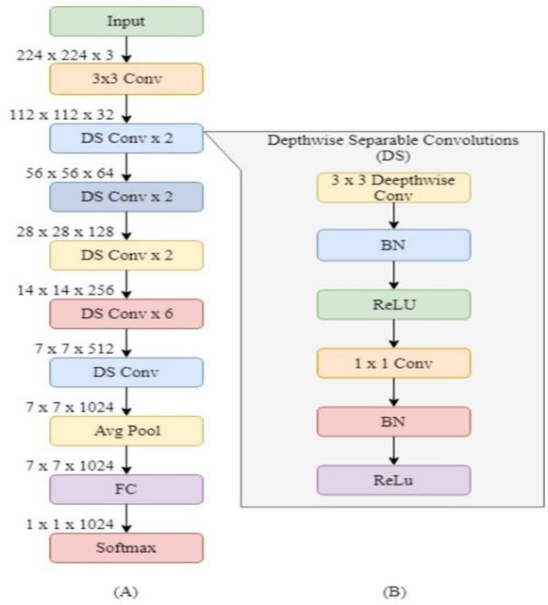

Fig. 5. MobileNet model architecture (A) The overall MobileNet architecture and (B) Depthwise Separable Convolutional layer[33].

4. Proposed System

Flood extent mapping can be achieved by classifying input images as per their severity level.

The architecture consists of following modules, which have been described in the next sections and the detailed proposed architecture is depicted in figure 6.

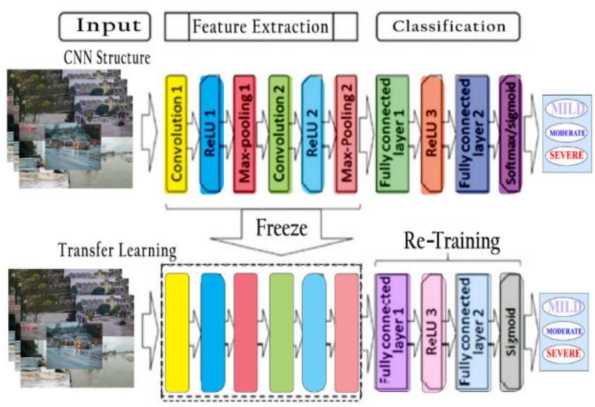

Fig. 6. Architecture of the proposed system

–Flood data collection

– Data cleaning

– Data labelling

– Training and classification (Multi class)

– Accuracy assessment

4.1 Flood data collection:

The dataset used for the research is self-created Indian flood image dataset. For supervised learning, the system needs training images capturing the flooded situation and which are annotated in advance. To the authors' knowledge, no comparable Indian flood image dataset exists currently. The dataset was created by gathering images with the categories flooding, flood, and floods from various web sources and individually taking the images while visiting actual flooded regions in India. The dataset consists of different view images of the area taken during a flood. Each image includes immersed objects (i.e., houses, people, and cars) along with water-level.

4.2 Data cleaning: The dataset is checked to remove duplicate images. At the same time, non-relevant pictures are extracted, and they are eliminated as well.

4.3 Data labelling:

After collecting and cleaning the data, it is carefully and manually categorized into mild, moderate, and severe categories.

4.3.1 Mild Class: When the condition is completely under control, the flood is in its early stages, with little or no influence on the surrounding area.

4.3.2 Moderate Class: When the situation is somewhat manageable, there is a minor impact on the locality (vehicles, persons, etc.) and mild infrastructure destruction.

4.3.3 Severe Class: Devastating impact on the locality (vehicles, people, etc.) as well as infrastructure and environment devastation.

The annotation of dataset task was given to the five different people and the majority of the class label for each image was considered as final class label. The sample images of each dataset are depicted in the figure 7.

Fig. 7. Sample images of three different categories of the dataset

4.4 Training and classification:

The proposed methodology is implemented using dataset developed from the Indian floods. When a classifier is developed on big datasets in a specific (source) domain, it generally increases the time complexity to get an accurate result. If the network is implemented to a different (target) domain that is unrelated to the source domain, it will take a long time to train. Transfer learning is now one of the strategies for improving the target domain's efficient prediction (e.g., run time reduction) [13]. For the target domain, transfer learning can make use of common domain knowledge from the source domain. A new effective approach in image classification is CNN combined with a transfer-learning methodology (CNN transfer learning). Training is done using pretrained models (VGG 16, MobileNet and ResNet 50) to achieve transfer learning.

Following are the common parameters used for training the three models.

Step 1. The dataset used in the research is our own developed dataset which has three classes labelled as mild, moderate, and severe. In total, 1842 images with on an average of 600 images per category have been used for further processing.

Step 2. Input flood images of varying size are transformed to (224 x 224 x 3) to input to the all the pretrained models. The reason behind resizing is that for reducing the computational time complexity and standard size required for the pretrained models.

Step 3. Split flood image dataset into training set and test set of ratios 80:20.

Step 4. Model the proposed pretrained network architecture.

Step 5. Tune the training parameters as adam optimizer, categorical-cross entropy loss function and learning rate = 0.001.

Step 6. Fit and train the data for mini batch size = 32 and run n number of epochs till validation loss reaches to its minimum.

4.5 Accuracy Assessment

Accuracy, Precision-recall and F1 score are the most widely used metrics for classification problems.

Accuracy can be defined as the ratio of correctly identified flood images to the total number of input flood images, as shown in Equation (1).

$$Accuracy = \frac{TP+TN}{Tp+FP+TN+FN} \quad (1)$$

where TP (True Positive) and TN (True Negative) represent the correctly identified flood images, while FP

(False Positive) and FN (False Negative) represent the incorrectly identified flood images.

Precision is the ratio of correctly identified flood images and the total number of flood images identified by the classifier as shown in Equation (2).

$$Precision = \frac{TP}{TP+FP}$$
(2)

Recall can be defined as the number of correctly identified flood images and the total number of flood images identified by the classifier as depicted in Equation (3).

$$Recall = \frac{TP}{TP+FN}$$
(3)

Similarly, the F1 score is defined as the harmonic mean of the model's precision and recall. The F1 score can be formulated in Equation (4):

$$\text{F1 score} = 2\,\text{X}\,\frac{Precision*RECALL}{Recision+RECALL}$$
(4)

In this research, the performance is evaluated using these metrics and compared the results with state of art technique [31] and achieved improvement in accuracy. This improvement can be explained due to variation in Model's architecture.

Table I: Properties of the CNN Pre-trained models

Sr. No.	Model	Size of the Model (MB)	Depth	Parameters (Millions)	Input Image dimension
1	ResNet 50	97.70	177	25.6	224x224x3
2	VGG 16	528	23	138.3	224x224x3
3	MobileNet	16	88	4.2	224x224x3

5. Results and Discussion

The analysis is performed on three pre-trained networks named ResNet 50, VGG 16 and MobileNet to find the severity of the flood. The networks are run various times to freeze the proper hyper-parameters viz. number of iterations, batch size, number of epochs and learning rate. Then for fitting the model on train dataset, training options are set as optimizer = adam, cost function = categorical-cross entropy and learning rate = 0.001 along with mini batch of 32 and on an average 10 epochs for each model. For experimentation three pre-trained models for identification of severity of flood by comparing the results with respect to classification accuracy is done. Table II shows the comparison between pre-trained models using average recall, precision, and F1-score. From Table II, it is evident that ResNet 50 pretrained network has improved the accuracy.

Table II: Comparison of Pretrained Models

Sr. No.	Model	Accuracy
1	ResNet 50	91.54%
2	VGG 16	85%
3	MobileNet	90%

The comparison of the present flood image classification work with the others [31], highest accuracy gained in the present work is 91.54% with ResNet 50 pretrained model whereas the highest accuracy achieved by authors [31] is 89%.

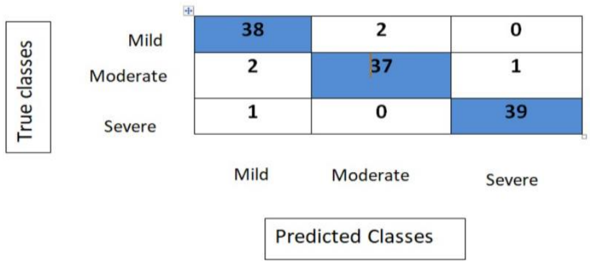

Fig. 8 Confusion Matrix of ResNet 50 model on test samples.

The confusion matrix of test samples for the proposed flood classification model using the CNN/ResNet 50 is presented in Figure 2. Further the performance measures like Recall, F1-score, precision, and accuracy are evaluated for all the three classes and for the overall model. These parameters are presented in figure 9.

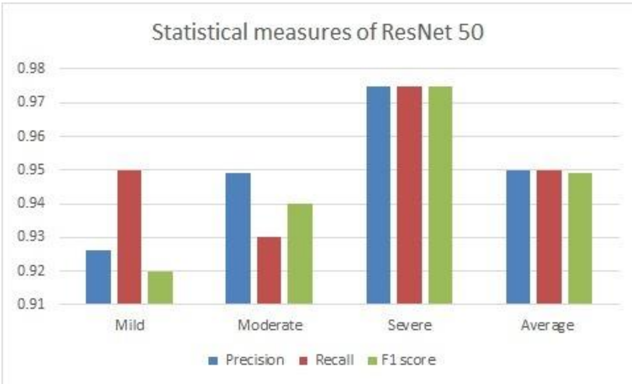

Fig. 9 Comparison of statistical measures of ResNet 50 for test samples**.**

From the experimental analysis, it is also observed that though the ResNet is a deeper network as discussed in table I still the vanishing gradient descent problem does not occur due to the fact that it is built by stacking residual blocks on top of one another and efficiently learning all the parameters from early activations deeper in the network.

6. Conclusion

In this research work, a new attempt is proposed for a flood severity classification using the CNN's three pretrained models, MobileNet, ResNet 50 and VGG 16. Experimentation is done on our own created Indian flood image dataset for three different classes. The proposed system assessed the performance of learning accuracy, recall, precision and F1 score for flood severity classification system. The results indicated that the pretrained network, ResNet 50 has achieved the accuracy of 91.54%. So, from this research work it can be concluded that, ResNets are one of the most efficient Neural Network Architectures since they help to keep error rate low even deeper down the network. As a result, it has proven to perform effectively in situations where deep neural networks are required, such as intricate feature extraction in flood image classification. In the future, this work will be extended on the lightweight pre-trained models to analyse computational complexity on the classification.

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