Full Paper

SOIL QUALITY DETECTION FOR UPLAND RICE FARMING USING PRE-TRAINED CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT
One of the most important factors that affect the yields of farm produce is the quality and usability of the soil. The analysis of the soil quality and the usability of rice, a staple crop in the world, have been of interest to many researchers. The increasing research in the field of upland rice farming is making it to gain more attention. The major challenge upland environment poses is soil suitability; due to the nutrient demand of rice plant. Convolutional Neural Network is a deep learning technique that is commonly applied in the analysis of visual imagery. This study has therefore used AlexNet, Inception V3, ResNet18 and GoogLeNet pre-trained convolutional neural networks to evaluate the usability of upland soils for rice farming. Soil samples and images were taken from Delta, Niger, Ogun and Osun states to the laboratory for analysis of soil PH and texture. Based on the soil quality score associated with each soil sample, the soil images were trained and classified as either "good for rice farming" or "not good for rice farming" using the selected pre-trained neural network. The results show high classification accuracy; however, ResNet18 performed best with an accuracy of 92.8%, slightly better than GoogLeNet. This studies further modified GoogLeNet model due to its portability to come up with a convolutional neural network model with an accuracy of 97.4%. Further research that explores additional soil parameters such as topography and moisture content is recommended.

Keywords: Convolutional Neural Network, Upland Rice Farming, Soil Quality

1. INTRODUCTION

The most important element in crop farming in the field of agriculture is the soil where crops are planted. The nature of the soil can go a long way to determine the degree of success achieved in farming. Therefore, vital properties of a soil have to be adequately considered and measured and before embarking on farming on any scale. Some of these properties include the pH of the soil, the macro and micro mineral constituents, soil structure, and its history. However, finding a method that delivers a high degree of accuracy of soil properties for rice farming is either sophisticated, time consuming or lacks reasonable accuracy. Rice is major cereal food crop produced globally. Upland rice farming is gaining more attention, as many research institutes now produces varieties that thrive in upland environment. However, one of the major challenges in upland rice farming is identifying a viable land (Mohammed *et al.*, 2019; Orluchukwu, Emem and Omovbude, 2019; Omoigui, Kamara and Kamai, 2020).

Testing soil is very important to anyone embarking on rice farming in upland environment. Unfortunately, lack of adequate knowledge, funds and technical skill may not afford a farmer the opportunity to carryout soil test (Kamble *et al.*, 2017). Most reliable tests are carried out mainly in Government or specialized laboratories at very high prices and are time consuming.

1.1. Upland Rice

An upland environment is a naturally occurring area that is not flooded or irrigated. It is an undulating or levelled naturally drained soil with water supply through rainfall. Nearly 100 million people now depend on upland rice as their daily staple food. Almost two-thirds of the upland rice area is in Asia. Bangladesh, Cambodia, China, Northeastern India, Indonesia, Myanmar, Thailand, Nepal, and Vietnam are important producers (USAID, 2017).

Upland rice is grown in rainfed fields prepared and seeded when dry, much like wheat or maize. The ecosystem is very diverse, including fields that are level, gently rolling or steep, at altitudes up to 2,000 meters and with rainfall within the range 1,000 to 4,500 mm yearly. Rice is undoubtedly one of the most consumed cereals in the world. It is of the grass species *Oryza sativa* (Asian rice) or *Oryza glaberrima* (African rice). With regard to human nutrition and caloric intake, rice is the most important grain. Globally, the 9th highest importer of rice is Nigeria while it remains the highest importer in West Africa. Main varieties of rice produced in Nigeria are Fadama, Upland and Lowland rice. The arrival of FARO 45 and FARO 46 which are early maturing in nature and also, the introduction of NERICA has fostered the cultivation of rice by farmers in upland environment. As a result, the mangrove environment is being less cultivated compared with upland rice (AgroNigeria, 2014; Nahemiah, 2017; Orluchukwu, Emem and Omovbude, 2019).

1.2. Soil Factor

Soil is made up of different proportions of sand, silt and clay. It exhibits several variations in its physical, mineralogical, chemical and biological properties. This is because soil is a heterogeneous unit. Knowledge of variability of soil properties is very crucial as this determines the productivity and usage of an area (Fageria, 2014; Dou *et al.*, 2016; Osujieke and Ezomon, 2019).

1.3. Convolutional Neural Network (CNN)

Convolutional Neural Network in the aspect of deep neural network that is commonly used in image data analysis. The input image is passed through convolution filters, also known as convolution kernels, where input features are extracted to provide outputs known as feature maps. It accepts an input and allocate weights and biases to it. CNNs have found great use in natural language processing, agriculture (fruit grading, leave disease identification, soil classification and many more), image segmentation, image classification, financial time series and brain-computer interfaces (Szegedy *et al.*, 2015). CNNs are a type of multilayer perceptron that are standardized. In multilayer perceptron, each neuron in one layer is connected to neurons in the next layer. The first approach in developing CNN was taken when an article concerning the visual cortices of birds and monkeys was released by Hubel and Wiesel. The process of convolution was initiated by Kunihiko Fukushima; it was called necognitron. It actually inspired the research of Hubel and Wiesel. Yann Le Cunn performed an outstanding work in the history of CNN as he brought CNN to the level it attained to da by developing a 7 level convolutional model named as the LeNet (Ajit *et al.,* 2020;Saha, 2018).

A CNN is basically made up of two parts:

1. **Convolutional Base:** made up of the convolution and pooling layers, the main purpose is to generate extract features from the input image.

Classifier: made up of one or more fully connected layers and possibly a softmax layer, the main aim is to classify the image based on the extracted features.

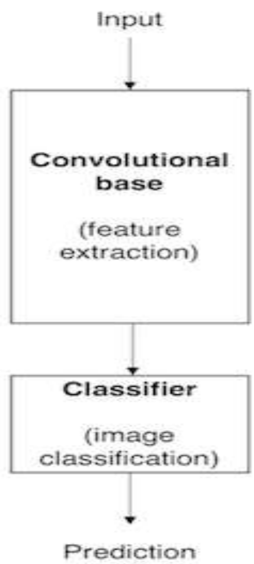


Figure 2: *Simple CNN Architecture (Sobti et al., 2021)*

There are different pre-trained CNN models. A pre-trained CNN model is one that is created and trained to solve a particular problem. The problem solved may be identical to a new research area therefore such model can be used in a new problem area, hence the term transfer learning. Some examples of pre-trained CNN models are VGG, GoogLeNet, AlexNet, LeNet, ResNet, SqueezeNet, Inception, DenseNet, DarkNet and so on (Ajit, Acharya and Samanta, 2020).

A. **AlexNet:** This pre-trained model was the winner of 2012 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). It has an input of 277x277 and was tested with ImageNet dataset of about 15 million RGB images. Identical to LeNet, it has 7 layers and 60 million parameters. It is made up of 2 fully-connected layers of 4096 neurons each, 11x11,3x3,5x5 convolutions and 3x3 max-pooling layers

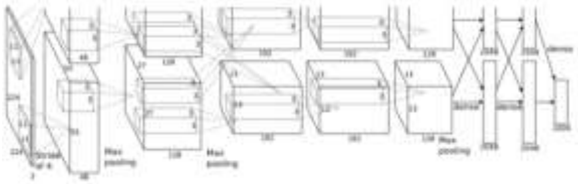


Figure 1: *AlexNet Architecture (Krizhevsky et al., 2012)*

(Jokhio and Jokhio, 2019).

B. **GoogLeNet:** This model was the winner of ILSVRC in 2014. Its backbone is the module known as the inception module. There are 9 inception modules in all, that is why GoogLeNet is referred to as network of networks. The inception module is made up of 1x1, 3x3,5x5 convolutions, 3x3 max-pooling layer, and concatenated feature output layer. It is 22 layers deep and has fewer number of parameters of about 5 million. The number of parameters is reduced because each convolution layer is preceded by a 1x1 convolution (Szegedy *et al.*, 2015).

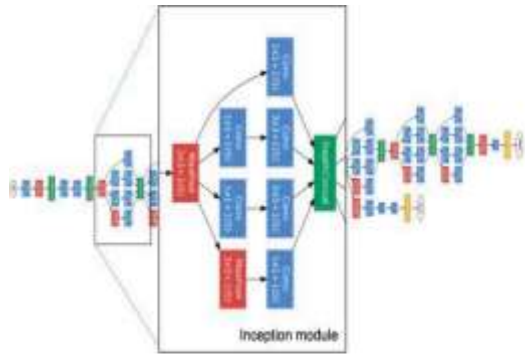


Figure 3: *GoogLeNet Architecture (Szegedy et al., 2016)*

C. **ResNet:** This was the ILSVRC winner for 2015, ImageNet challenge. The version used at the ImageNet challenge had 152 layers; deep network. It exceeded human accuracy with about 3.6%. It used skip connection feature to solve the problem of vanishing gradient as performance dropped when the network got too deep. The input and output of one layer is copied to the next, in order words, learning the residual computation of the previous layer. At the end of each

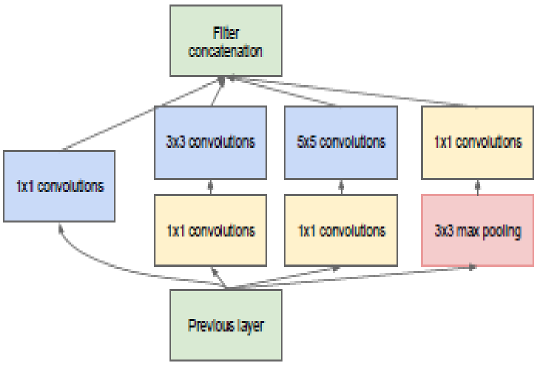


***Figure 4**: Inception Module with reduced dimensions*

convolution is batch normalization, and about 65 million parameters were computed (He *et al.*, 2016).

D. **Inception V3:** This is from the family of inception models. With auxiliary classifier, factorized 7x7 convolutions, and label smoothing, it has quite a number of reasonable modifications. The aim of factorizing convolutions is to limit number of parameters without attenuating efficiency of the

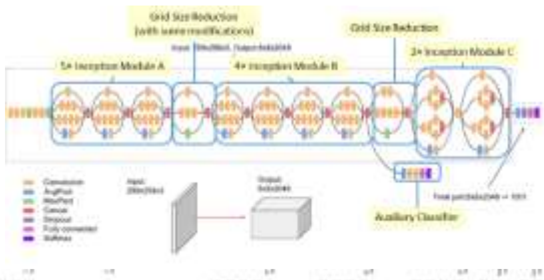


***Figure 6**: Inception V3 Architecture (Tsang, 2018)*

***Figure 5**: ResNet Architecture (He et al., 2016).*

network. The model is 42 layers deep but has a higher cost of computation compared with GoogLeNet (Szegedy *et al.*, 2016)(Tsang, 2018).

2. REVIEW OF LITERATURES

Soil quality is regarded as the capacity of a soil to function. The assessment of a soil focuses on various aspects of the soil in order to measure the sustainability of soil management practices. (De La Rosa and Sobral, 2008) explored arable land identification, variations in crops, replenishment of organic matter, concentration of tillage, and justification of soil input. The quality of a soil is either inherent or dynamic in nature.

(Venkat Narayana Rao, 2019) worked on predicting soil quality using machine learning techniques. The paper suggests a solution in consideration of vital soil attributes and factors in order predict the soil quality. The researcher used amongst other testing algorithms Random Forest Algorithm, and using regression to increase efficiency. However, the prediction turned 70% accurate as revealed in resulting confusion matrix. Researchers (Aitkenhead *et al.*, 2016) designed a neural network model that is capable of estimating soil structure, texture, bulk density, pH and drainage category. The model provides estimates of these parameters from soils in a field. Each soil image (in their JPEG format) was converted to digital values and stored as three arrays of red, green and blue pixel values (with values ranging from 0 to 255). To achieve comparable levels of accuracy, models would need to be developed that are more applicable to regions of interest. This may be almost impossible for many areas of the world as there are no mapped information. Therefore, the method applied here is largely dependent on data availability, from soil surveys and partial datasets with appropriate accuracy.

(Kamble *et al.*, 2017) implemented the calculation of soil pH using digital image processing. Eighty soil samples were collected and test in government laboratory. The work used digital image processing to determine the pH of the collected samples on the basis of RGB values. The work provided report of soil tested with likely deficient nutrient. They obtained results of about 60 to 70% accuracy compared with the values from government laboratories. The analysis of soil pore spaces is very useful in interpreting soil structure. This is mainly because soil physical and physiochemical parameters can be influenced by pore space.

A fuzzy system was successfully designed by (Abu, Nasir and Bala, 2014) in order to control soil pH. The input to the system consisted of humidity, light intensity and temperature. The fuzzy method was used with Matlab software. The system also recognizes temperature, humidity and lighting changes. The prototype system was designed by Matlab software to perform simulation, the method yielded unstable results.

The works of (Riese and Keller, 2019; Anami, Malvade and Palaiah, 2020; Liang *et al.*, 2020) made use of one or more pre-trained or modified pre-trained convolutional neural network. (Riese and Keller, 2019) used ResNet on Lucas dataset and had a result of 70% accuracy while (Anami, Malvade and Palaiah, 2020) used VGG16 model and obtained a classification accuracy of 95.08%. (Liang *et al.*, 2020) among other methods used AlexNet and VGG19 to test land usability with remote sensing and had 95% classification accuracy for AlexNet and 91.8% classification accuracy for VGG19 method.

3. METHODOLOGY

The aim of this work is to use pre-trained CNN to test the usability of soil sample images for upland rice farming. The study will also proceed to modify an existing pre-trained CNN to derive and architecture more suitable for the dataset and obtain best possible result.

3.1. Dataset

Part of the soil samples were collected from Bida in Niger State, Osogbo in Osun state, Abeokuta in Ogun state and Warri in Delta state, Nigeria. Sixty-one (61) soil samples were collected observing standard procedure. The samples were analyzed in a laboratory at National Cereals Research Institute (NCRI), Badeggi Niger State, Nigeria. The pH values and textures of the samples were measured in the laboratory. Soil sample photos were taken in-situ during the day with a digital camera of 720 x 1600 resolution and 13 megapixels. In order to improve results and make feature extraction process easier, the pictures were taken without foreign materials like stones and plants, thus making almost any part of the image potential region of interest. As seen in literatures, the pH indicates the presence of certain chemical components in the soil while the texture reflects the water retention capability of the soil. Upland rice varieties thrive in soils within the pH range of 5.5 to 6.5 and soil texture with particularly high clay content required for water retention. After laboratory analysis of the sixty-one samples collected, sixteen were found to be good for upland rice farming while the remaining forty-five aren't good for upland rice farming. The remaining 662 soil samples were gotten from United Stated Geological Survey (USGS) database. The dataset is divided into two, 506 training set with 111 good for upland rice and 395 bad for upland rice farming. The second part of the dataset is 217 samples which is the testing set; 48 of them are good for upland rice farming while the remaining 169 are not good for upland rice farming.

***Table 1**: Summary of Dataset*

Soil Dataset			
	Total	**Good for Rice**	**Bad for Rice**
Training Set (70%)	506	111	395
Testing Set (30%)	217	48	169
Total	723	129	564

The dataset has been grouped based on soil factors which include pH and texture. Soil samples with pH within the range of 5.5 to 6.5 and texture of 40% clay content is classified as good for rice farming and the ones outside that condition are classified as not good for rice farming. This can be represented mathematically as:

Let the pH of a soil sample be represented as H

Let T be texture and sand, silt, and clay be sa, si, and cl respectively. Then,
T is a tuple such that
$T = (sa, si, cl)$ and
$sa \wedge si \wedge cl \subseteq T$
There are two classes represented by C1 and C2
C1 represents the class of soil samples that meet criteria for upland rice farming
C2 represents the class of samples that do not meet the criteria for upland rice farming
Conditions for C1 is given by:

$$sa, si, cl \in C1 \Leftrightarrow cl \geq 4 \quad (1)$$

$$H \in C1 \Leftrightarrow 5.5 \leq H \leq 6.5 \quad (2)$$

$$\therefore T \wedge H \in C1 \Leftrightarrow cl \geq 40 \wedge 5.5 \leq H \leq 6.5 \quad (3)$$

Conditions for C2 is given by:

$$sa, si, cl \in C2 \Leftrightarrow cl < 40 \quad (4)$$

$$H \in C2 \Leftrightarrow H < 5.5 \vee H > 6.5 \quad (5)$$

$$\therefore T \wedge H \in C2 \Leftrightarrow cl < 40 \wedge (H < 5.5 \vee H > 6.5 \quad (6)$$

Figure 7: *Figure. 7. Sample Dataset Collected*

3.2 Implementation

The dataset will be used on 4 pre-trained CNN which are AlexNet, ResNet18, Inception V3 and GoogLeNet. The results will be compared and then GoogLeNet will be modified for better performance. The work in this study was implement in Matlab 2020a environment. The process flow of the method is given below.

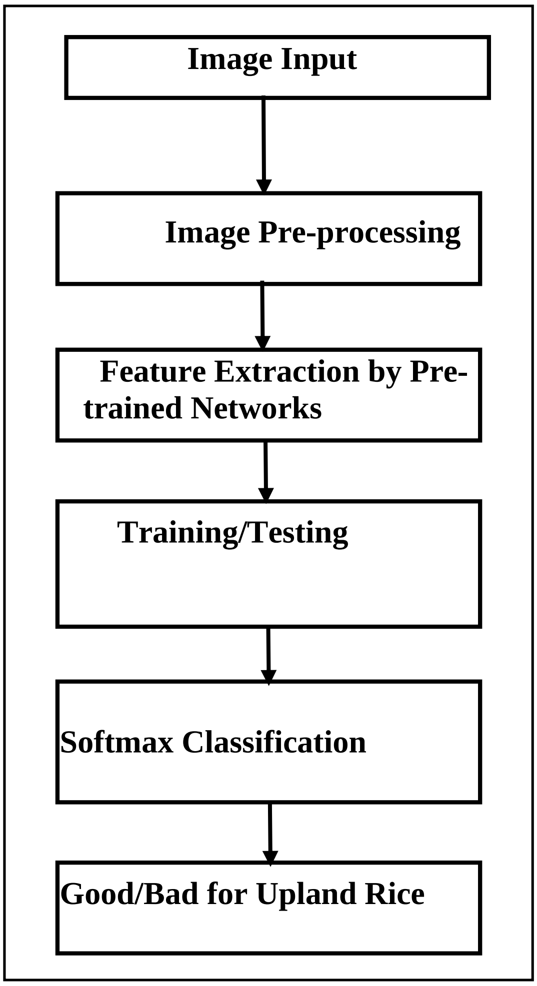


Figure 8: *Block Diagram of Pre-trained Network Process*

3.3 GoogLeNet Modification

In order to achieve better result, a model was developed inspired by GoogLeNet architecture. The inception layers were modified. Inception Module is the micro architecture in which the GoogLeNet macro architecture is built on. There is a total of 9 inception layers, each inception layer is made up of 1x1, 3x3, and 5x5 convolution filters and max pooling layer. The number convolution filters were modified to 3×3, 5×5, 7×7, 9×9, 25×25 and 28×28. Increasing the convolution filters allowed for lower-level and higher-level feature extraction from the images which in turn resulted in

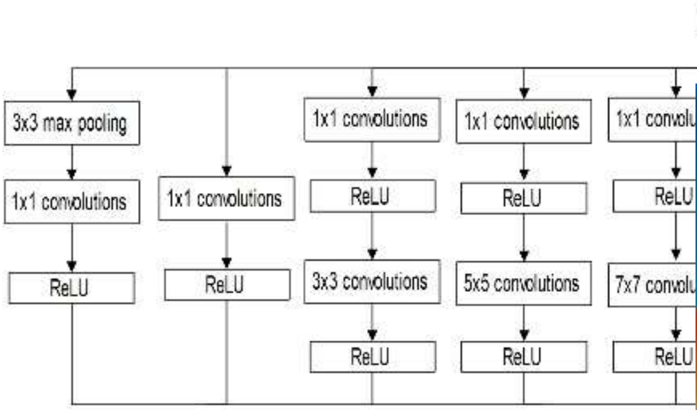
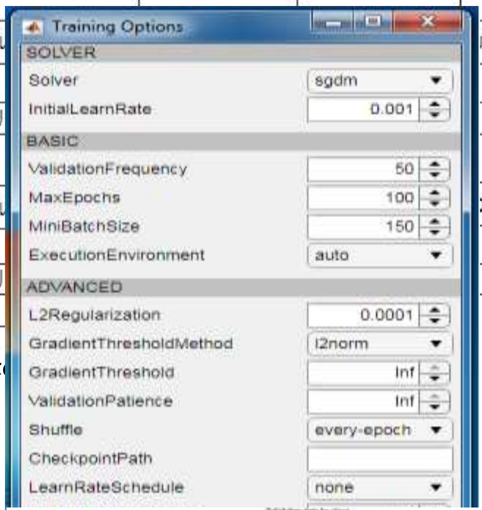


Figure 9: *Modified GoogLeNet Inc*

better model performance and higher accuracy. Furthermore, since GoogLeNet is designed to handle 1000 different object categories (classes) and millions of datasets, further modifications can be made since this study has only two categories and limited dataset, the inception modules were reduced until the model performance began to drop. At 5 inception modules, the model had the best result. The original inception module is shown in Figure 4.

The Figure below shows the network parameters that were fine-tuned in Matlab environment.



Training and validation data by their classes as generated in Matlab environment are given below.

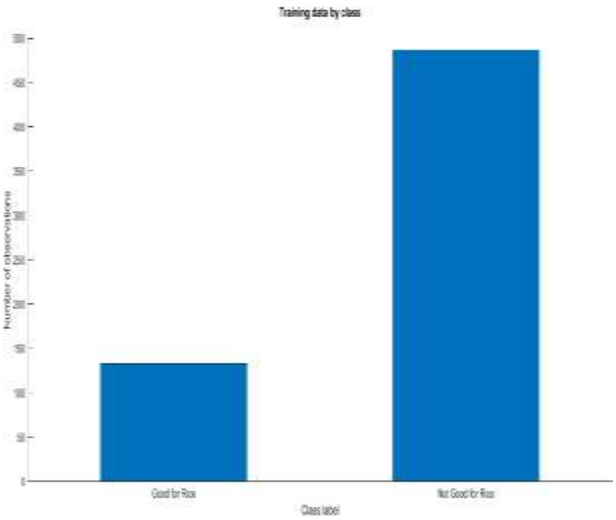


Figure 11: *Training Data by Class*

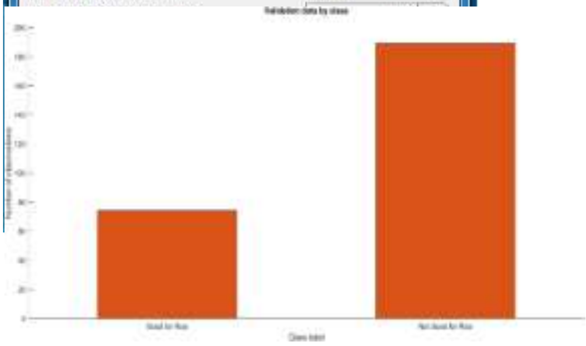


Figure 12*: Validation Data by Class*

After modifying the inception modules and reducing them to just 5, the Figure below shows the final architecture of the proposed model.

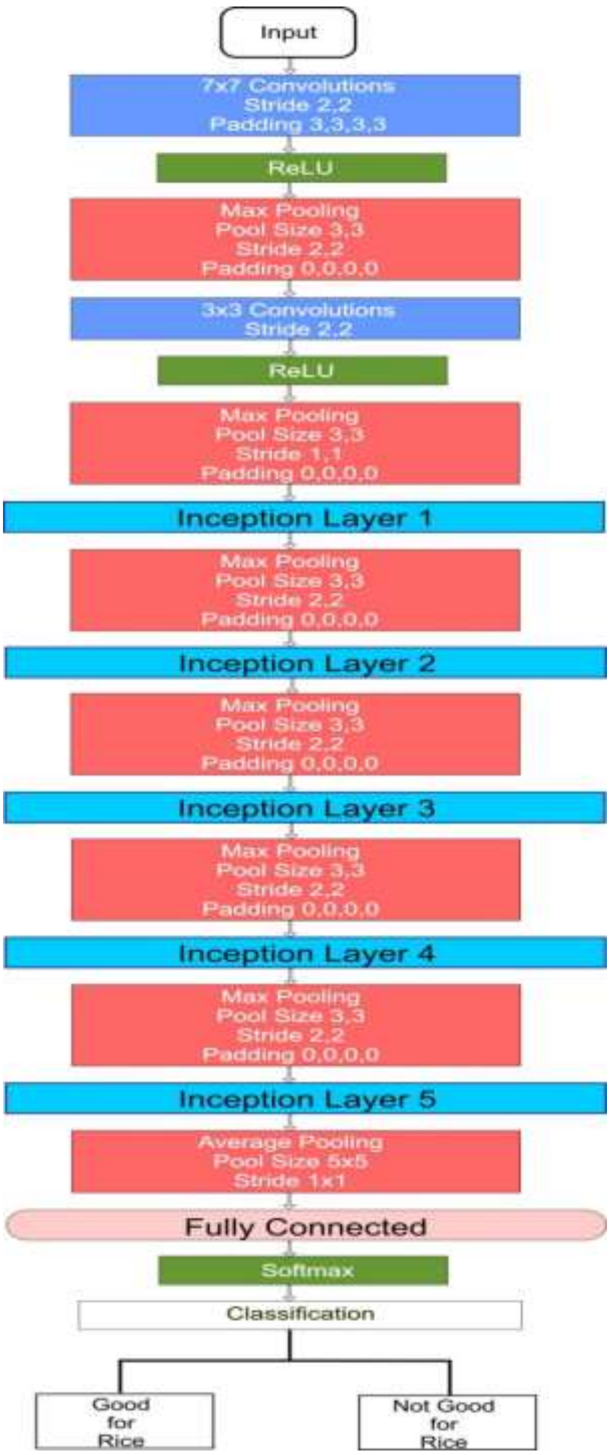


Figure 13: *Modified GoogLeNet Architecture for Rice Soil*

4. RESULTS

Inception V3, AlexNet, ResNet18 and GoogLeNet models were used on the dataset training and testing. The result of the training and testing is given in the following images.

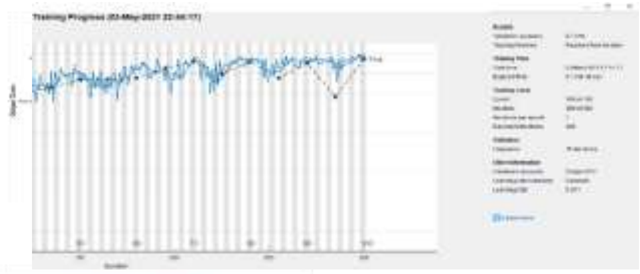
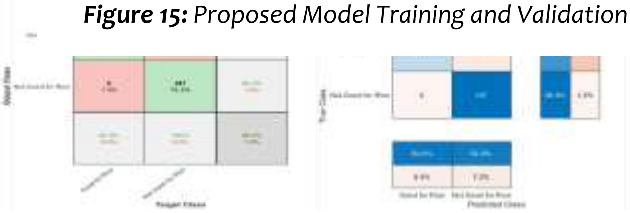


Figure 15: *Proposed Model Training and Validation*



(c) (d)

(e) (f)

(g) (h)

Figure 14: Training and Testing Images of 4 Pre-trained Networks: (a) Confusion Matrix of AlexNet on Training Dataset
(b) Confusion Matrix of AlexNet on Testing Dataset
(c) Confusion Matrix of ResNet18 on Training Dataset
(d) Confusion Matrix of ResNet18 on Testing Dataset
(e) Confusion Matrix of GoogLeNet on Training Dataset
(f) Confusion Matrix of GoogLeNet on Testing Dataset
(g) Confusion Matrix of Inception V3 on Training Dataset
(h) Confusion Matrix of Inception V3 on Testing Dataset

The table below summarizes the training and testing results for the 4 pre-trained models and proposed model.

Table 2: *Training and Testing Results Of 4 Models*

	Network				
	Alex Net	Res Net 18	GoogLe Net	Inception V3	Model
Training Result	98.4%	98.7 %	99.8%	100.0%	100.0%
Test Result	77.9%	92.8 %	92.7%	91.8 %	97.4%

The results show that the proposed model performed better with an accuracy of 97.4 %.

5. CONCLSION

This study was able to develop a model that detects a soil's suitability for upland rice farming. The work leveraged on existing pre-trained algorithms which uses transfer learning. Of the four tested algorithms, ResNet18 performed better. However, GoogLeNet was modified to suit this case study. GoogLeNet inception layer and number of inception modules were modified. It was observed that increasing the number of convolutions in the inception module yielded better results. Also, the addition of 1x1 convolutions to each inception layer improved performance and reduced computational parameters. The model showed an overall accuracy of 97.4% which performed better than other tested networks. Increasing the number of convolutions also increases the chances of getting a better result, however, this usually comes with a cost of increased computation cost and complexity of network. In order to address these disadvantages, 1x1 convolutions was carried out before passing the image through every other convolution layer as seen in *Figure 9*. When compared with other literatures explored in this study, for example the works of (Utaminingrum and Robbani, 2016; Venkat Narayana Rao, 2019; Anami, Malvade and Palaiah, 2020; Liang *et al.*, 2020), this study's model is lighter, faster (in training and testing), and has better accuracy.

Further studies would consider increasing dataset and including additional soil parameters such as topography and moisture content.

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