CLASSIFICATION OF ALL-PURPOSE SAND: A DEEP LEARNING APPROACH

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Abstract - Construction sand classification is an essential process in the construction industry. The proper classification of sand plays a crucial role in determining the quality and suitability of sand for specific construction purposes. In general, sand is classified based on its particle size, shape, texture, and colour. Understanding these characteristics can help builders and contractors choose the right sand for their projects.The particle size of sand can also be classified using the Unified Soil Classification System (USCS), which categorizes sand as poorly graded, well-graded, and uniformly graded. In the building sector, differentiating sand based on its texture would be very beneficial as it will save builders, contractors, and construction workers a lot of time and work and speed up their process, resulting in higher efficiency and better results. One such model, which is actually a combination of three different pre-trained deep learning models, is proposed in this study combining machine learning and deep learning approaches. Based on the collection of images that are given to it, the model assists in classifying the sand. The results demonstrate that the first model used, Densenet-169, provided approximately 92% of accuracy, while the other two models, Inception V3 and Xception, provided approximately 85-90% accuracy. The weighted average ensemble model provided the best accuracy of 98%, which was actually the best we got.

I. INTRODUCTION

Construction, mining, and agriculture are just a few of the many industries that employ sand categorization. It entails classifying sand particles according to their size, shape, and other attributes. Sand classification is essential for various processes, including figuring out whether or not sand is suitable for concrete, filtration, or soil stabilization.

Sand is categorized according to the size of its grains, which range from very fine to coarse sand. Sand can be classified in a variety of ways according to various criteria, but the process is difficult. This procedure is essential to guarantee that the sand fits the requirements for the intended use and helps prevent any potential issues that may occur from utilizing inappropriate sand. Sand is frequently used in construction to add strength, mass, and stability to materials including concrete, mortar, asphalt, and cement.

But not all sand is created equal; some of it has rocks and other impurities that reduce its stability and toughness for use in the building process. The most typical types of sand used in construction include concrete sand, pit sand, natural or river sand, manufactured sand (M-sand), utility sand, and fill sand. These sands are suitable for a range of construction applications due to their distinctive properties.

Our research is focused on the automated classification of different qualities of all-purpose sand, the most used sand for construction in the nation.The manual separation of sand using a strainer is labour-intensive. The separating process may be automated to save time and labour. The proffered work will assist in automating this tiresome procedure.

Convolutional neural networks have undergone significant development over time and are now at the center of the majority of contemporary picture categorization issues. Since picture datasets are bigger than non-image datasets, it is computationally expensive to take into account every pixel in an image. However, due to the high degree of redundancy in photos, it can be crucial to reduce image size without sacrificing crucial elements. This is achieved using CNN's filters and pooling layers. As a result, deep learning methods can be used to produce a reliable categorization.

Transfer learning helps a CNN model become more accurate and efficient while also shortening its training period. This article employs deep learning procedures to automate the classification process.There is not much work done on sand image classification [1] performed 2D Greyscale image classification using VGGNet, ResNet, and Inception models with the highest accuracy of 98.24% by Inception-V3.

The findings demonstrate that sand samples with intermediate shape criteria are less accurately categorized than those that are mostly round and irregularly shaped [2] on the other hand used machine learning for the classification of the sand particles. Seven models were applied to 2000 binary images of each type of sand. Numerous intriguing conclusions were taken from this investigation. It is noted that both of the articles, most relevant to our study, make use of single sand grain images for their experiment. Bridging the identified gap, this article focuses on the cluster of grains rather than a single-grain image.

Using the cluster of grains will reduce the automation task on multiple levels without compromising the accuracy of the system.

Major contributions of the study are:

- A novel dataset consisting of 336 images of different types of all-purpose sand.
- A classification system with acceptable accuracy, employing deep learning models and ensemble techniques.

It is important to categorize the various types of construction sand, in order to determine its use (plastering, masonry, etc.). Sand segregation is a time-consuming and labour-intensive task that can be automated with the help of the system proffered in this article. The system may find its use in studying different types of sand without the aid of an expert.

The organization of the article is as follows. The following section gives the detail of the dataset and its creation. Section 3 provides methodology. Section 4 provides results and discussions. Finally, ending with conclusions in section 5.

II. DATASET DESCRIPTION

2.1. Background

There are seven different varieties of sand, but only a few of them are employed in construction work, and others are unsuitable owing to their nature. The created dataset consists of three distinct types of sands that are primarily used in brickwork, plastering, and other sorts of construction.

Depending upon the quality and the texture, the sand is divided into grades, namely grade 1, grade 2, and grade 3. Both "Sand for masonry" and "Sand made from crushed stone" are other names for these classifications of the sand (all-purpose Construction sand). The three primary forms of sand used in construction are river sand, crushed sand, and pit sand.

Typically, riverbanks are used to gather river sand, whereas deep ditches are used to mine pit sand. On the other hand, crushed sand is created at quarries by purposefully crushing (to fine particles) rocks. Grade 2 sand is obtained from the riverbed, which is also referred to as all-purpose sand because it can be utilized for all projects aside from plastering. It is most frequently used in construction because it gives bricks, concrete, and other building materials strength.

After a small amount of separation or segregation of the impurities, Grade 1 sand is created. The best sand is grade 1, which is utilized in plastering since it is the finest and free of any contaminants that the other two grades might have. Because of its poorer quality than the other two and contains different pebbles and stones, grade 3 is the worst kind of sand to use in building projects hence it is utilized in areas where high-quality sand is not required.

For instance, it is used at homes to create a barrier outside buildings to prevent water from penetrating them and weakening their structural beams. The main objective of the automated classification of sand is to reduce the amount of labour work necessary to discern between the sand produced by crushing rock and the sand that is recovered in vast quantities from riverbeds.

2.2 About the Dataset

This section describes a novel dataset ClaSan that has been created as a part of this research work to perform the automated detection and classification of different types of sand (all purpose construction sand). The dataset is made up of 336 images that were taken around the state of Jharkhand, primarily in a local processing facility for sand in Neori under expert supervision.

These 336 images were further augmented as data augmentation was done on these images to make them more suitable for training for the model and to achieve better results. The dataset includes three different classes of sand based on quality and additional characteristics such as texture, color, etc. Grades 1, 2, and 3 sand are categorized as class 1, 2, and 3 respectively. Table 1 gives a brief summary of the dataset and its distribution along the classes.

Class	No. of images
Class 1	104
Class 2	112
Class 3	120
Total	336

Table 1: Number of images per class for the ClaSanDataset

2.3. Dataset Creation

The dataset that was constructed utilizing photos obtained from the Sand processing site had a size of 4612 x 2600 at first, however, this size was later decreased by preprocessing and modification. To account for heterogeneity in the dataset, the images were captured under slightly varying illuminating conditions. Experts distinguished between the many classes of sand before taking pictures while maintaining a constant distance between the sand and the camera.

The images were taken on different timings of the day The size and quality of each image are the same, at 64 megapixels and 1.7 aperture, respectively. Figure 1. gives a sample of the images.

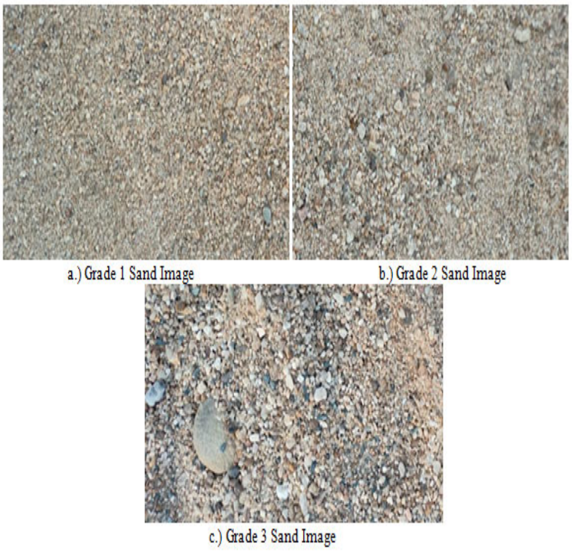


Figure 1: A sample from the ClaSan dataset showing images of Class 1, Class 2 and Class 3 types of Construction Sand.

III. METHODOLOGY

The many procedures involved in performing the picture classification of sand kinds utilising transfer learning, average ensemble, and weighted ensemble are described in depth in this section. The ClaSandataset, a brand-new dataset developed for this research project, is the one that was used. We present the model architecture in this section. Pre-processing is done initially to the incoming dataset. The dataset is expanded by doing image augmentation. The accuracy scores generated by these base learners separately calculate and output are crucial for our average ensemble model's accuracy score.[6],[7] These three fundamental learning models are very significant because we will use them in our average ensemble and weighted ensemble model, which considers their scores and then determines accuracy, which may or may not be higher than the fundamental models. Refer Fig.2 for the architecture of the weighted average ensemble model.

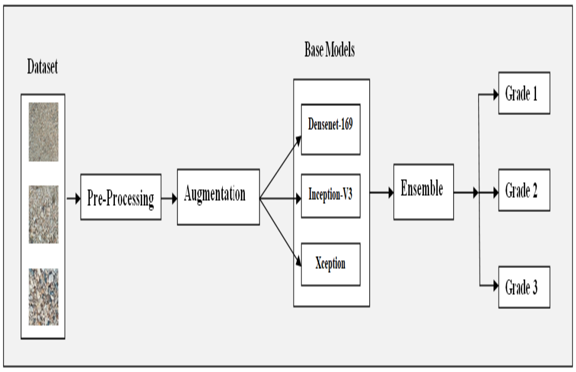


Figure 2. Architecture of the weighted average ensemble model

3.1. Preprocessing

The pre-processing step resizes the input images to 256 x 256 x 3, which is required size for the input to the model. The sand images originally present in this dataset are 4612 x 2600 x 3 in size which were collected from the site in Neori, Ranchi. The images have been resized to 256 x 256 x 3 for this study. The dataset is split into training and test sets in a 70:30 ratio to get a decent enough result. The number of images present in the training and test sets is given in the below table. Table 2. describes the split of the dataset.

Class of Sand	Training Set	Testing Set
Grade 1	72	32
Grade 2	78	34
Grade 3	84	36
Total	235	101

Table 2: Number of images present in train set and test set after splitting the dataset in 70:30 ratio.

3.2. Image Augmentation

CNN models require a large amount of training data to build a robust, more accurate, and powerful model. Image augmentation provides the model with a very large supply of images so even small datasets can perform well enough with augmentation. The images for which class label prediction has to be performed are not always in the same orientation. Hence image augmentation allows the CNN model to learn with changes in location, shifting, rotation, etc., which significantly increases the performance and robustness of the model. Moreover, augmentation allows the model to train for a greater number of epochs without overfitting and as we know if we increase the number of epochs we might get a better result as compared to the epochs being low in number. All these features of image augmentation makes it a very useful and a powerful technique for image classification problems. The image augmentation has been performed on the training set to increase the amount of data that is input to the model for training. The various image augmentation transformations that have been performed on the brick images are briefly mentioned below.

Rescale: The images are rescaled by multiplying them with a 1/255.0 factor before any other processing. Originally, the pixels in the images were in the range 0-255. Rescaling converts these values between 0 and 1 and hence performs the normalization.

Rotation: The images are rotated in the range of 0 to 90 degrees.

Shifts: The shift translates the images as per the specified range either horizontally or vertically. The width shift and height shift range are set at 0.2.

Flip: The images have been flipped horizontally and vertically.

Fill mode: Nearest pixel fill mode has been used to fill the new pixels created after the application of variousThe above data augmentation methods or transformations have been performed using the Python Keras package in Jupyter Notebooks

3.3. Pre-Trained Model

Densenet-169: Densenet is a deep learning model which embraces the observation that convolutional networks with a shorter connection between layers near input and output are deeper, accurate, and efficient to train . For a maximal flow of information between layers, apart from connection with preceding layers to preserve the feed-forward nature of the network, it also connects all layers with the same feature-map size directly with each other. [3] Its default input size for Densenet-169 is 224 × 224 × 3, therefore a customized input layer has been added, which sets the input shape to 256 × 256 × 3. Inception V3: Inception v3 is one of the most used deep learning models. It uses the idea of auxiliary classifier, factorization into smaller convolutions, spatial factorization into asymmetric convolutions, RMSprop optimizer, batch normalization, and model regularization via label smoothing to show better accuracy results [4].

It takes an image of size 299 × 299 × 3 as input and passes it through different convolution and pooling layers to finally perform flattening and then uses softmax in the output layer to perform the classification. Xception: Xception, which stands for the extreme version of Inception, has a modified depth-wise separable convolution. The point wise convolution is followed by a depth wise convolution in the modified depth wise separable convolution. This change is inspired by the inception module in Inception-v3, which performs 1x1 convolutions before any n x n spatial convolutions. Xception does not use intermediate ReLU non-linearity, since the highest accuracy was achieved without any non-linearity compared to those using ELU or ReLU. The default input image size for Xception is 299 x 299 x 3. [5]These base models were chosen because they provided the best accuracy results for us. For example, we applied many models, such as MobileNet v2, VGG16, and Resnet-50, but these 3 pre-trained models provided the best accuracy results for us, so we decided to create an ensemble model out of these 3 pre-trained models [6],[7],[8].In comparison to independent base learners, the model using Average Ensemble produces a better classification outcome. We used a different version of the ensemble model a weighted average ensemble which assigns weights to the model that has provided us with the best accuracy. We also used many other different models with this ensemble technique, but we discovered that these three pre-trained models produce the best results [9],[10].

3.4. Training Hyper parameters

The classification of sand based on texture requires rigorous training on the dataset. The input layers of the models are customized to take input images of size 256 × 256 × 3. A fully connected layer of 1024 neurons with ReLU activation function were added for all three base learners followed by a dropout of 25%. Then we use another fully connected layer, for which we have 256 neurons with ReLU activation function for each of the three base learners. And finally, for the output layer, we have 4 neurons along with the softmax activation functions, which outputs the required accuracy score for our model. Because the categorization of the construction sand is based on texture and therefore it needs rigorous and prolonged training on a big dataset, the number of epochs utilised for fine-tuning the model for the dataset has been set to 10. The hyperparameters used in training the CNN models are summarized in table 3.

Hyperparameter	Value
Input shape	(256,256,3)
Pooling	Average
Weights	ImageNet
FC Layer 1	1054 neurons
Dropout	0.25
FC Layer 2	256 neurons
FC Layer activation function	ReLU
Output Layer	4 neurons
Output Layer activation function	Softmax
Optimizer	RMS Prop
Learning Rate	2e-5
Loss Function	Sparse Categorical Crossentropy
No. of Epochs	20
Steps per epoch	18
Batch Size	32

Table 3 Detailed description of the Hyperparameter values.

3.5. Dropout Tuning

The model was tested with various dropouts and it was observed that 25% dropout gave the best result (see table 5), ergo the experiment was conducted with

25% dropout. Table 4. shows the model accuracy with different dropouts.

Dropout	Densenet-169	Inception V3	Xception
0.15	0.92	0.87	0.89
0.25	0.98	0.93	0.92
0.35	0.92	0.93	0.88

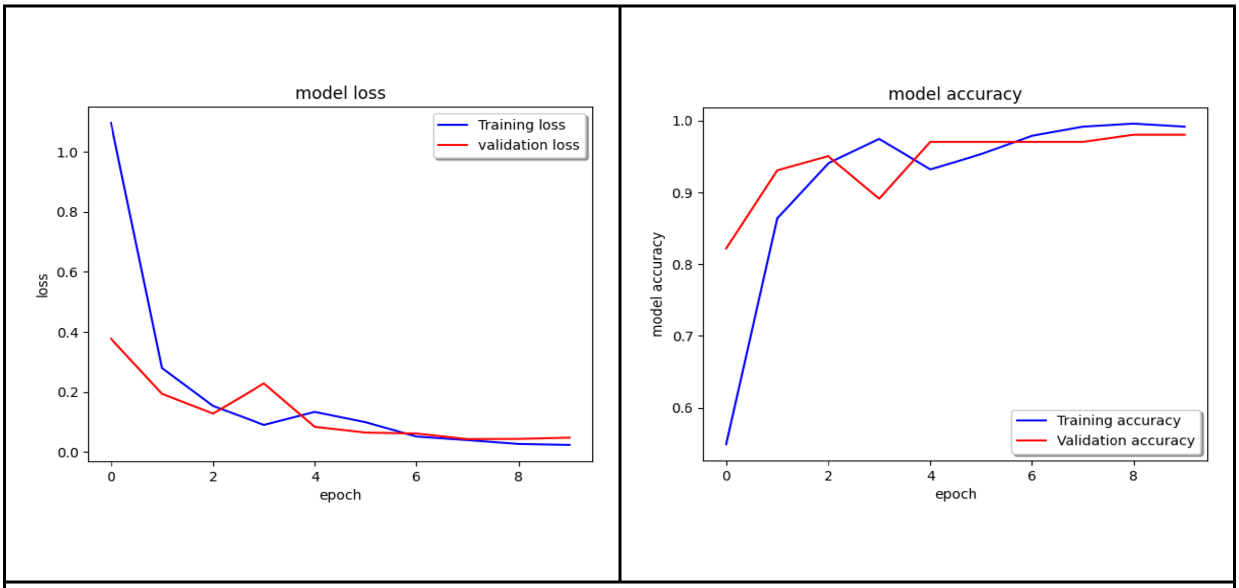
Table 4: Model accuracy with different dropouts

IV. RESULTS AND DISCUSSION

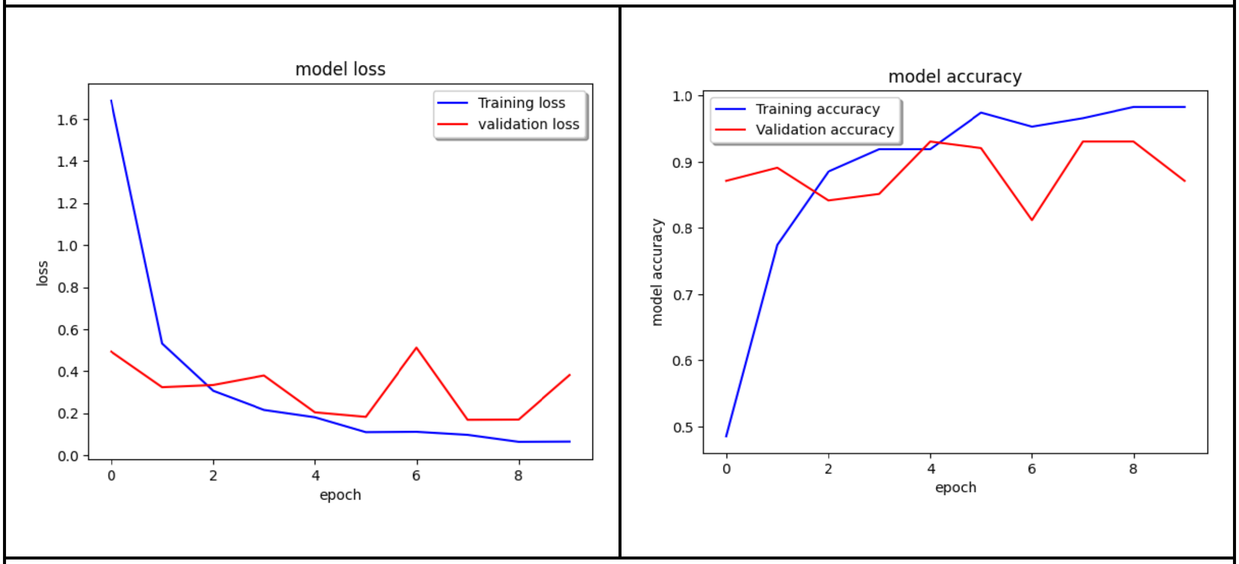
4.1. Results

The results of the three base models and the weighted average ensemble model on construction sand (all-purpose sand) type classification are presented in this section.

Acomparison between the base learners and ensemble model based on accuracy, precision, recall, and f1-score is also discussed in this section.



(a)



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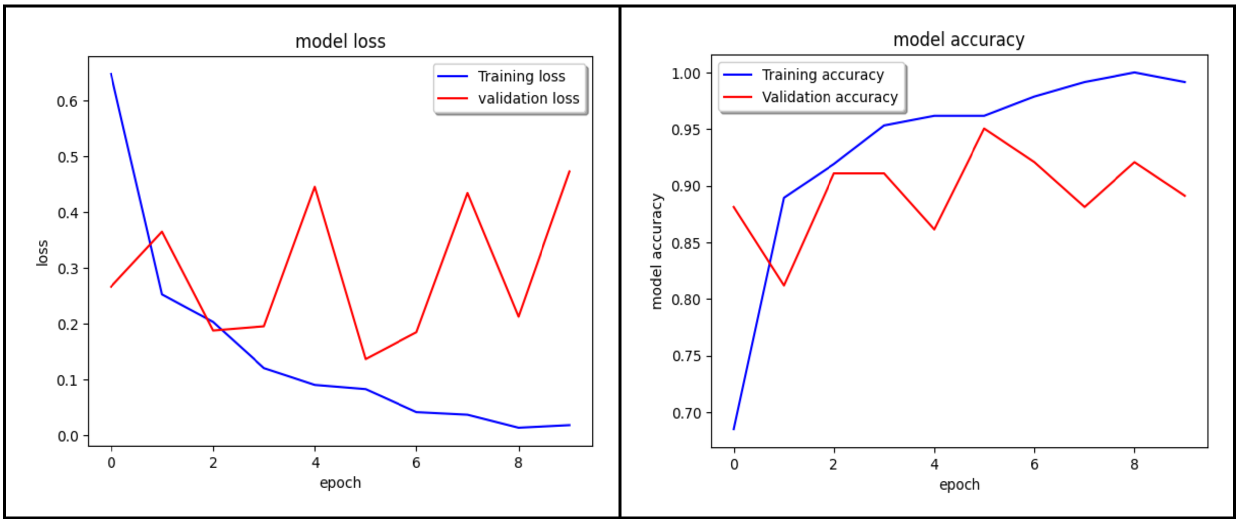


(c)

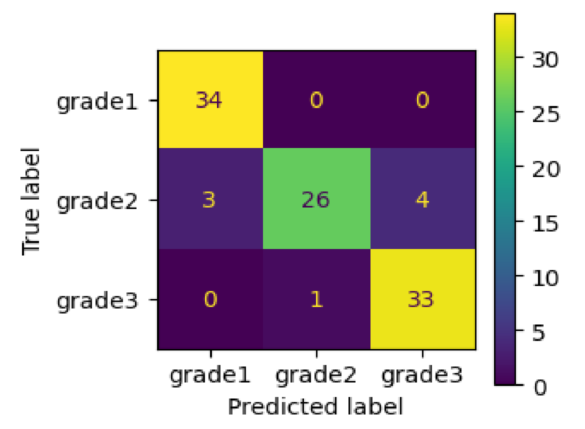
Fig. 3. Loss and Accuracy Graphs for (a) Densenet-169, (b) Inception-V3, and (c) Xception Models

From the Fig. 3 it can be seen that Densenet-169 gives the highest accuracy among the base models on the ClaSan dataset. From the classification report shown in Table 5, it is evident that the ensemble model gives the highest accuracy of 98% and has the highest F1 score for all three classes as compared to Inception V3 and Xception. But it can be noted that the ensemble model is in close proximity to the Densenet-169, in terms of performance. The Xception model gives an accuracy of 89% and the Inception-V3 gives an accuracy of 87%. The Xception model has a higher f1 score than Inception V3.

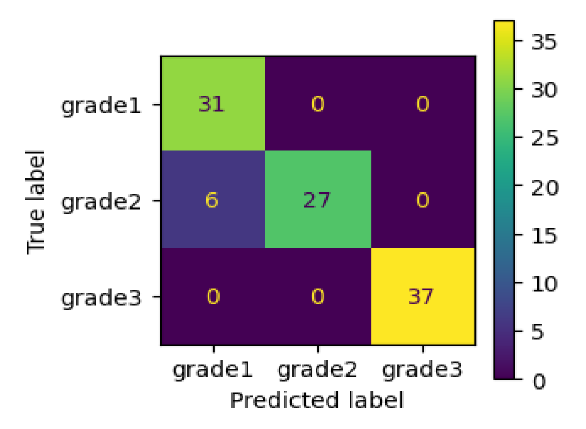
Densenet-169				
Class	Precision	Recall	f1-score	Accuracy
Grade 1	1.00	0.92	0.97	0.92
Grade 2	0.93	0.93	0.96	
Grade 3	1.00	0.97	0.95	
Inception-V3				
Class	Precision	Recall	f1-score	Accuracy
Grade 1	0.95	0.95	0.95	0.87
Grade 2	0.69	0.93	0.79	
Grade 3	1.00	0.76	0.86	
Xception				
Class	Precision	Recall	f1-score	Accuracy
Grade 1	1.00	0.92	0.96	0.89
Grade 2	0.71	1.00	0.83	
Grade 3	1.00	0.78	0.88	
Ensemble model				

Class	Precision	Recall	f1-score	Accuracy
Grade 1	1.00	0.97	0.99	
Grade 2	0.93	1.00	0.96	0.98
Grade 3	1.00	0.97	0.99	

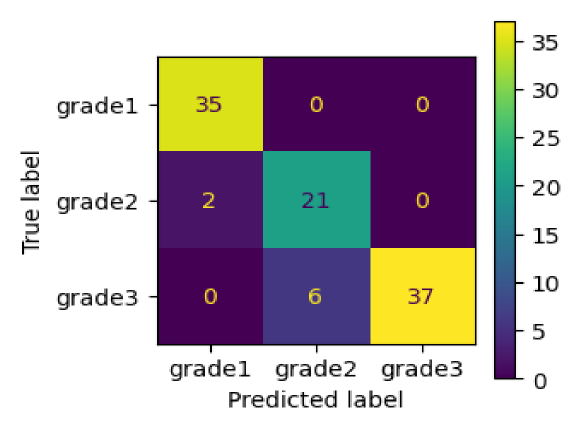
Table5. Evaluation parameters for the models



(a)



(b)



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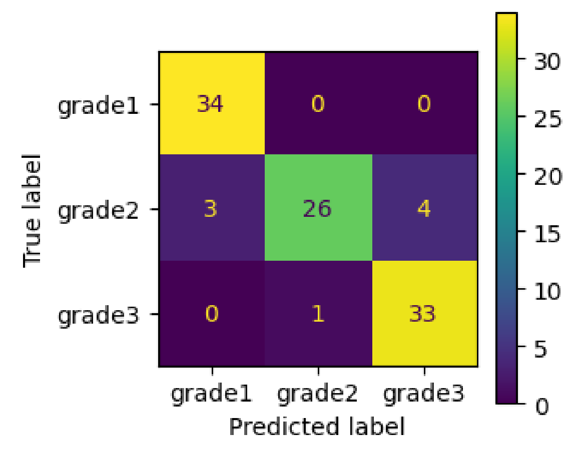

(d)

Fig. 4. Confusion matrix for (a) Densenet-169 Model (b) Inception-V3 model (c) Xception model (d) ensemble model

It is evident that the ensemble with base models Densenet-169, Inception-V3, and Xception gives better accuracy of 98% as compared to individual models. The confusion matrix for all of the base models can be seen in Fig. 4

V. CONCLUSION

Classification of the construction sand is very important as it helps us to reduce the human effort in this process of dividing the sand depending upon its quality and it speeds up the construction work process of the building or anything that is being made. In this research, we have made the ensemble model which will divide the sand on the basis of its images taken from the field.

The results have demonstrated that the classification work done on the dataset has been successful, with an acceptable accuracy of 98% attained using an ensemble model. The study is limited to 336 images which can be extended further. Apart from the count, the dataset is also limited in terms of regions covered and types of sand covered in the study which is to be extended as part of future study.

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