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Deep learning for the prediction and classification of land use and land cover changes using deep convolutional neural network

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A R T I C L E I N F O

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A B S T R A C T

The importance of timely and accurate information about the land resources and the natural resources increased rapidly. Due to the impact of urbanization, the we face hasty climatic change. To mitigate the urban heat island in the developed and developing cities, a very accurate land cover classification has to be developed. Through which we can identify the changes in build-up areas, water bodies and vegetation index. In this paper, a hybrid hot encoding VGG19 deep learning method has been proposed. And a transfer learning method has been used to transfer the training data trained by the RestNet50 method to the proposed HGVGG19 method. The satellite images and aerial images are collected from various sources and classified based on the features. And the image dataset has been pre-processed using the image augmentation technique. Through which the image has been resized and processed for training it with the proposed mode. The categorical data cannot be processed directly, so we use one hot encoding method to find the borders of the class. Then the data has been trained using VGG19 method. Then using the MLR classifier we classify the images and using decision tree the class prediction has been predicted. After testing the model an accuracy of 98.5% has been achieved. Using the proposed algorithm, the analysis has been made with the historical images of many regions. And eight different class values have been obtained and stored as the textual data. Using the data, the land cover changes and the prediction of the land cover has been obtained with an accuracy of 98.5%.

1. Introduction

The changes in the land use and land cover in the urbanized cities make a huge impact in the climatic change. Based on the data provided by National Remote Sensing Centre by Indian Space Research Organisation, in India in the last ten years the percentage of build-up area has been dramatically increased. In some developing states like Tamil Nadu, when compared to other states the percentage of build-up area was increased more. In Tamil Nadu, Chennai is the most populated city, it is considered for hub for many businesses and Coimbatore is the next level of development. Thus, we need to identify the changes in the land cover with more accuracy for mitigating the impact of it. Due to this impact the temperate is increasing and rainfall is decreasing gradually. Based on the deep learning methods, more accurate prediction can be done. When Convolutional Neural Networks (CNN) models were used in tasks like image classification, object detection, and facial recognition, Deep Learning had a major effect on the field of computer vision. Ce Zhang et al. (Zhang et al., 2020) suggested a straightforward and parsimonious Scale Sequence Joint Deep Learning (SS-JDL) approach for joint LU and LC classification, in which a sequence of scales is inserted in the iterative process of fitting the joint distribution inherent in the joint deep learning (JDL) method, thus replacing the previous model of scale selection. Using the architecture of tensorflow, Jian Xiao et al. (Xiao et al., 2020) used an enhanced convolutional neural network VGG-19 algorithm to identify illicit activities of workers without masks in workplaces and heavily populated areas, collecting over 3000 images for model training and testing. Three FC layers are optimised into one flat layer and two FC layers with reduced parameters using the VGG-19 network model. A 2-label softmax classifier replaces the original model's softmax classification sheet. The model's accuracy is 97.62%, and its recall is 96.31%, according to the experimental data. The accuracy of distinguishing employees without masks is 96.82%, the recall is 94.07%, and the data collection given is highly precise. Venkatesan Rajinikanth (Rajinikanth et al., 2020) and colleagues suggested that a deep learning architecture (DLA) be developed to enable the automatic identification of brain tumours using two-dimensional MRI slices. The following DLAs was proposed for detecting the BT in this study: I pre-trained DLAs with deep-features-based classification using decision tree (DT), k nearest

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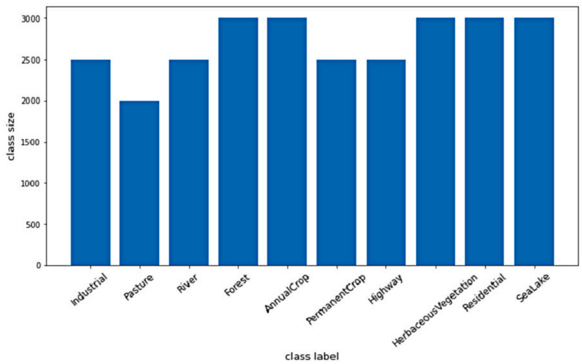

Fig. 1. Classification of testing and training dataset.

neighbour (KNN), SVM-linear, and SVM-RBF; (ii) a customised VGG19 network with serially-fused deep-features and handcrafted-features to improve the BT detect; and (iii) a customised VGG19 network with serially-fused deep-features and handcrafted-features to improve the BT The experimental investigation was carried out separately using MRI slices from the Flair, T2, and T1C modality, and a ten-fold cross validation was used to verify the performance of the proposed DLA. Two parameters must be addressed while training an SVM using the Radial Basis Function (RBF) kernel: C and gamma.The parameter C, which is shared by all SVM kernels, trades off misclassification of training instances for the decision surface's simplicity.A low C smoothes the decision surface, whereas a high C attempts to accurately categorise all training instances. The gamma value indicates how powerful a single training example is. The greater the gamma, the closer the other instances must be in order to be influenced. The findings show that combining VGG19 and SVM-RBF improved classification performance for Flair (>99%), T2 (>98%), T1C (>97%), and clinical photos (>98%). DeepLabv3+, as proposed by Liang-Chieh Chen et al. (Chen et al., 2018), adding a simple decoder module to the segmentation results by extending DeepLabv3, especially along boundaries of an object. And, using the Xception model, apply depthwise separable convolution to both the Atrous Spatial Pyramid Pooling and the decoder modules, resulting in a faster and more efficient encoder-decoder network. The proposed model performed well on the PASCAL VOC 2012 and Cityscapes datasets, with test set results of 89.0% and 82.1%, respectively, without any post-processing. Christopher D. Storie et al. (Storie and Henry, 2018) investigate the use of deep learning neural networks (DLNN) to analyse satellite imagery, with a particular emphasis on the development of land use/land cover charts. Over the past few years, DLNN has made significant progress in pattern analysis and machine learning. Since the technique was initially designed for simple photos rather than satellite imaging, the remote sensing implementation is less well defined. The findings of an experimental study that established a DLNN to produce land use/land cover maps of Manitoba's southern agricultural area are presented in this article. When compared to a human-based semi-automated procedure, the findings of this approach indicate a strong improvement in processing time once the DLNN is properly trained. Using deep learning technologies, Hanfa Xing et al. (Xing et al., 2018) suggested a framework for using geo-tagged images for ground cover validation. The method began by automatically identifying images using the VGG-16 network. Following that, samples for validation were chosen and further categorized based on the distribution of images and classification probabilities. The implementations were carried out in a heterogeneous region of western California in order to validate the GlobeLand30 land cover product. The experimental findings demonstrated promise in ground cover validation, with GlobeLand30 achieving an overall precision of 83.80% with graded samples, which was similar to the visual perception validation outcome of 80.45%. The efficiency of deep learning based on ResNet-50 and AlexNet was also measured, with no significant variations in final validation results. When opposed to just considering the single closest photo, the suggested solution ensures geo-tagged photo consistency and supports the sample classification technique by considering photo distribution, with accuracy improving from 72.07% to 79.33%. As a result, the

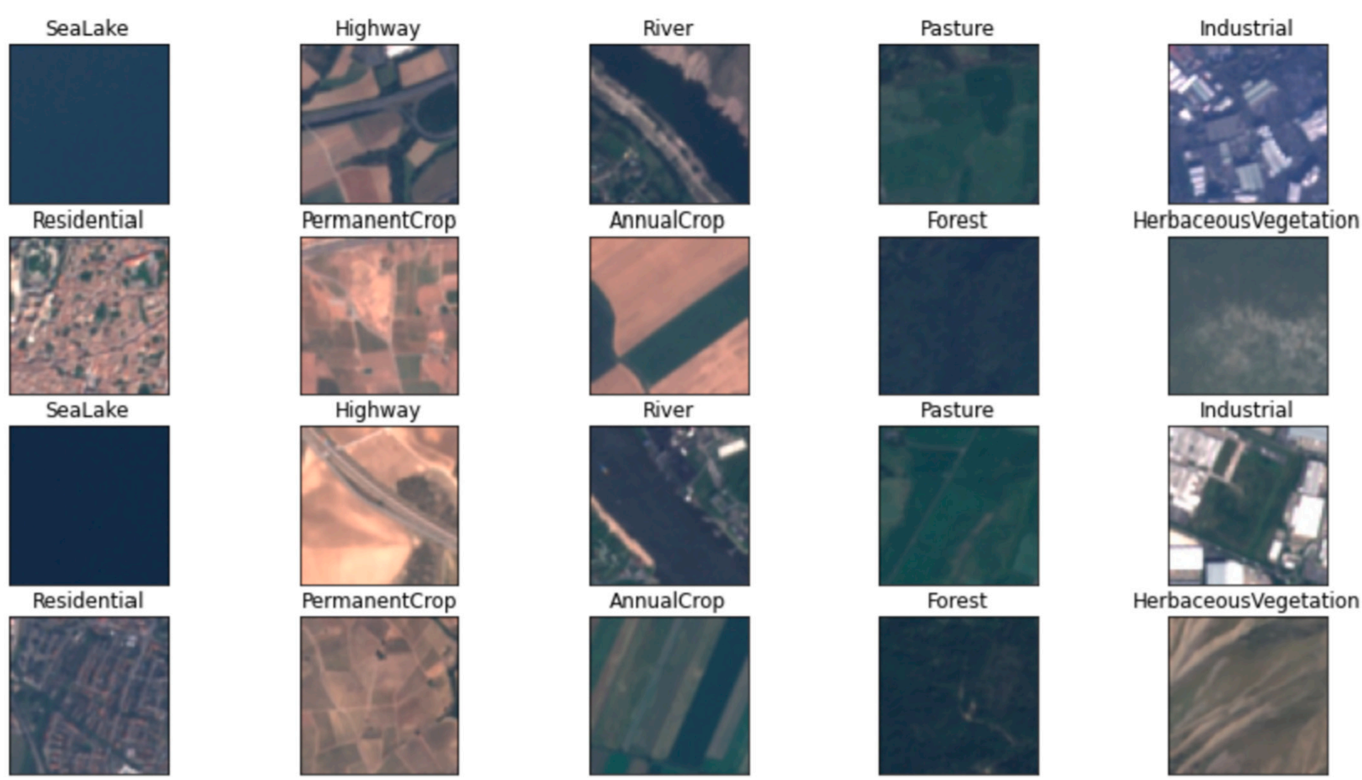

Fig. 2. Classification of sample training dataset.

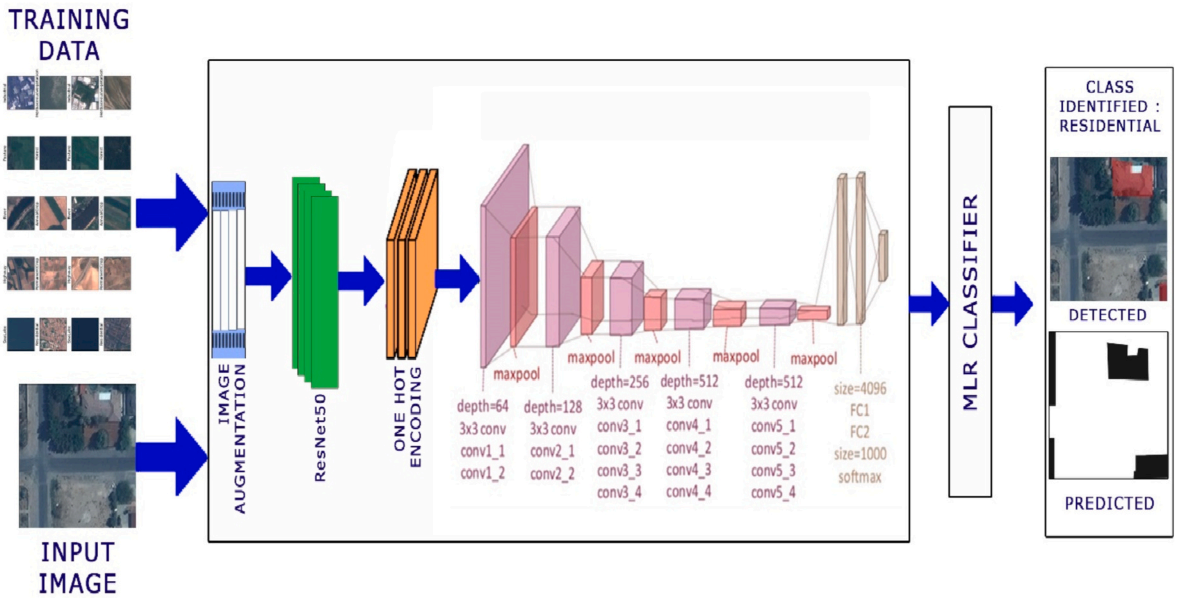

Fig. 3. Architecture of HEVGG19.

Fig. 4. One hot encoding.

proposed method shows the viability of deep learning technologies for defining land cover details in geo-tagged images, and it has a lot of potential to aid and enhance the performance of land cover validation. Tiago Carvalho et al. (Carvalho et al., 2017) suggest a modern technique for finding inconsistencies in extremely realistic computer generated images by looking at inconsistencies in the eye area. These discrepancies are captured by analysing the expression capacity of features derived using the VGG19 Deep Neural Network model and a transfer learning approach. Unlike current methods, which analyse the whole image, the proposed method focuses on small regions (eyes) where computer graphics modelling still needs to be improved. Experiments on two separate datasets containing incredibly realistic images yielded an accuracy of 0.80 and an AUC of 0.88, respectively. Karen Simonyan et al. (Simonyan and Zisserman, 2014) examine the effects of convolutional network depth on image recognition accuracy at a wide scale. Our key contribution is a detailed assessment of networks of increasing depth using an architecture with very narrow convolution filters, which reveals that pushing the depth to 16–1 weight layers achieves a major improvement over prior-art configurations. We also prove that our representations generalise well to other datasets, producing state-of-the-art outcomes in the process. To encourage more study on the use of deep visual representations in computer vision, we have made our two best-performing ConvNet models publicly accessible. Inception modules in convolutional neural networks are interpreted by Franc ois et al. (Chollet, 2017) as an intermediate stage between normal convolution and the depthwise separable convolution operation (a depthwise convolution followed by a pointwise convolution). In this way, a depthwise separable convolution can be thought of as an Inception module with the most towers possible. This discovery leads us to suggest a new deep convolutional neural network model based on Inception, but with depthwise separable convolutions in lieu of Inception modules. Kaiming He Xiangyu et al. (He et al., 2016) propose a residual learning system for training networks that are significantly deeper than previously used networks. Instead of learning unreferenced functions, we directly reformulate the layers as learning residual functions in regard to the layer inputs. We provide detailed empirical data demonstrating that residual networks are simpler to optimise and can gain precision from substantially increased depth. We test residual nets with a depth of up to 152 layers on the ImageNet dataset, which is 8 deeper than VGG nets (Amar et al., 2021) but also has lower complexity. On the ImageNet test range, an ensemble of these residual nets reaches 3.57% error. On the ILSVRC 2015 classification challenge, this outcome took first place. We also display CIFAR-10 analysis with 100 and 1000 layers. For certain visual perception tasks, the depth of representations is important. We achieve a 28% relative boost on the COCO object detection dataset solely due to our incredibly deep representations. Deep residual nets are

Fig. 5. Localisation of buildings.

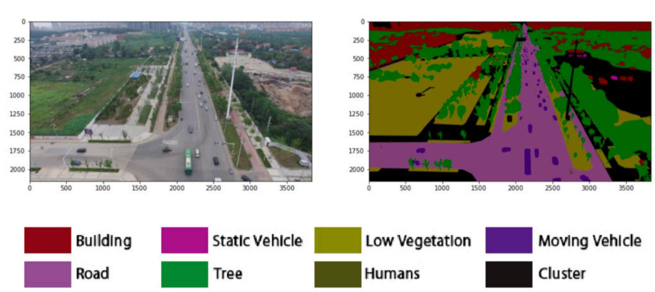

Fig. 6. Land cover change - classification.

at the heart of our submissions to the ILSVRC and COCO 2015 competitions1, where we also took first place in the ImageNet identification, ImageNet localization, COCO detection, and COCO segmentation assignments. The study in Traore (2021) discovered a positive relationship between NDBI and LST, as well as negative relationships between LST and NDVI and NDLI. To reduce the impact of surface urban heat islands (SUHI) on the city and its environs, city planners should build urban green belts and green roofs. The models used in (Mansour et al., 2020) this study might be used not only as spatial guides for monitoring future LULC dynamics, but also to address challenges to urban sustainability in Omani mountain towns. Thomas (Gasser et al., 2020) proposed a unifying method based on the application of an empirical constraint and a bookkeeping model that embeds processes and parameters calibrated on dynamic global vegetation models.

2. Methods

The land-use and land-cover classification for the remote sensing image obtained for various regions and the testing of the prediction algorithms was done for the regions of Chennai and Coimbatore based on some well defined target class labels (Aggarwal et al., 2020; Gao et al., 2020; Rajmohan et al., 2020). For training the model we will use the dataset obtained from the National remote sensing centre and using the open-source data provided by google. Sentinel-2 satellite images could also be downloaded with 10+ additional bands. Near-Infrared Radiation bands, for example, is a band of data that is available for this dataset. This dataset consists of 64 × 64 satellite images and it has over 27,000 images spread across 10 classes. The images has been divided in to 80–20 split for the purpose of training and testing.

2.1. Data exploration

The dataset collected has been explored. This dataset lists images of the earth's surface into 10 different land cover labels. For this, an image

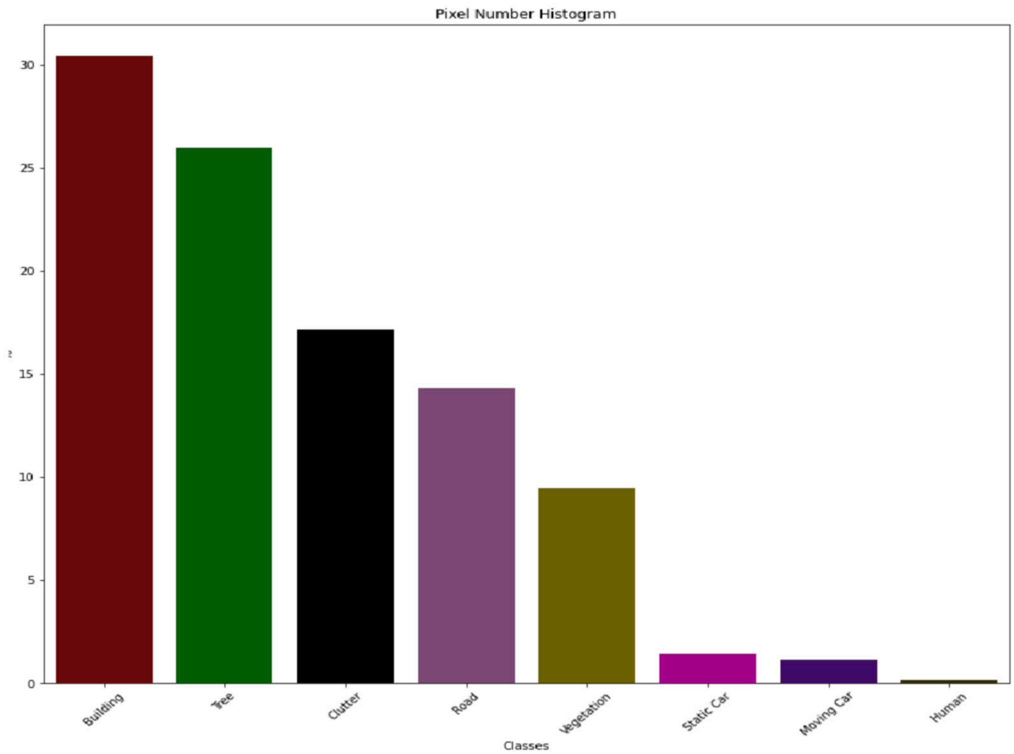

Fig. 7. Classification of values based on land cover image.

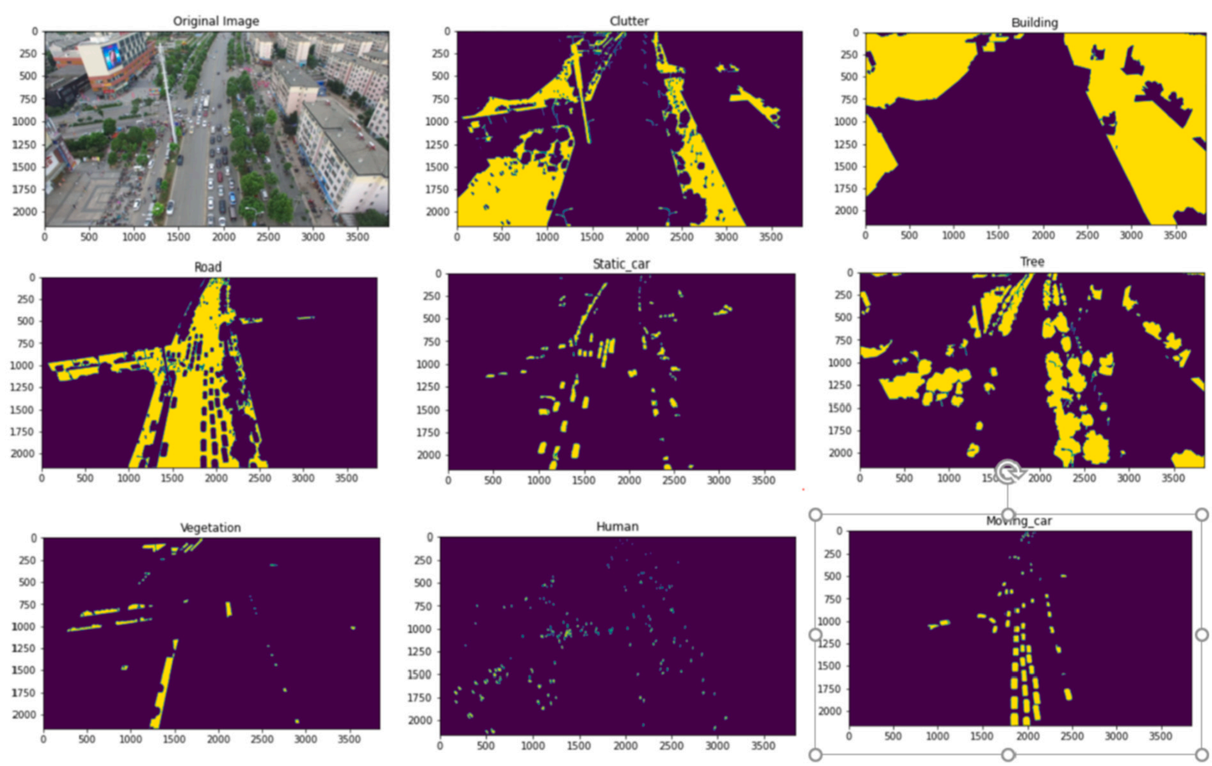

Fig. 8. Segmentation of each classes in to different mask.

classification model for predicting a land cover label has been build.

The dataset was divided into 10 land cover classes. Each class have a various number of images. So the images are divided in to training and testing set based on the count of images in each classes. The sample images has been displayed for each classes. We can see some similar and blunt difference between the classes. From the sample dataset we can identify, in urban environments such as Residential areas, Industrial Areas and Highways contains the structures and some roadways. Some agriculture land cover areas like Annual Crops and Permanent Crops defining different crop fields. Some, Herbaceous Vegetation like Pasture

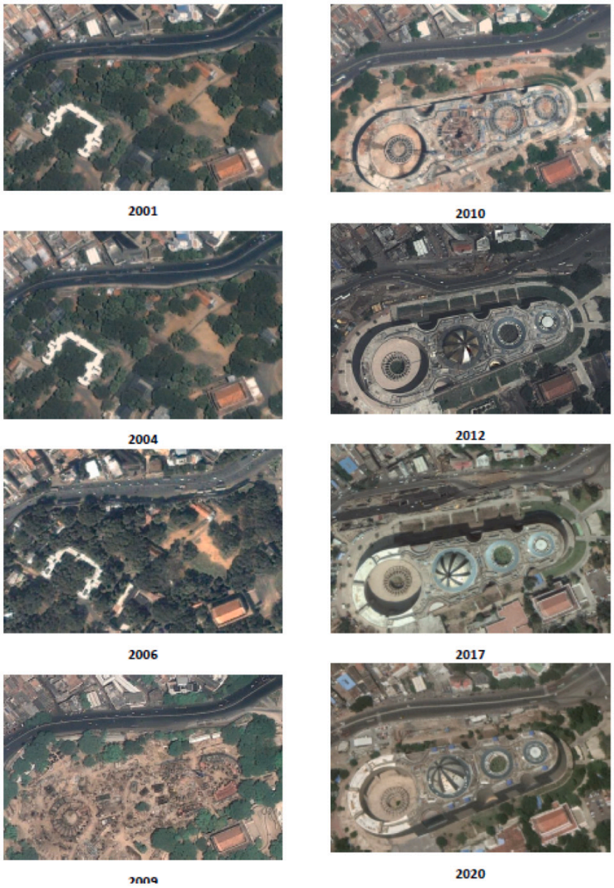

Fig. 9. Historical images of a location in Chennai – from 2001 to 2020.

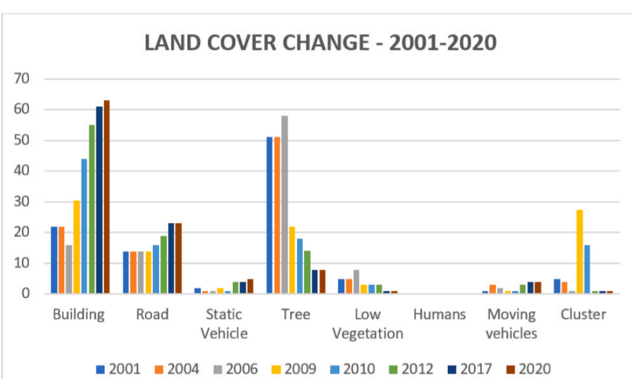

Fig. 10. Land cover change based on the data obtained from the image in Fig. 9.

and Forests feature natural land cover; Rivers also could be categorized as natural land cover as well, but may be easier to distinguish from the other natural classes.

The practise of shooting images from an aircraft or other flying object is known as aerial photography. Fixed-wing aircraft, helicopters, unmanned aerial vehicles, balloons, blimps, and dirigibles, rockets, pigeons, kites, parachutes, and stand-alone telescopic and vehicle-mounted poles are all used for aerial photography. Mounted cameras can be remotely or automatically activated, and hand-held photos can be shot by a photographer. Earth photographs and other photos shot from the air and space reveal a lot about the planet's landscapes, flora, and resources. Remotely sensed pictures, which include aerial and satellite photos, allow for precise mapping of land cover and make landscape characteristics intelligible at regional, continental, and even global sizes. By comparing pictures taken at different periods, transient phenomena such as seasonal vegetation vigour and pollutant discharges may be examined.

We may be able to estimate which groups are likely to be confused if we look at the content of each image. Image of a river may be mistaken for a highway. A image of a highway intersection with buildings in the background may be mistaken for an industrial site. We will need to train a classifier that can distinguish between these differences.

2.2. Pre-processing

To evaluate the performance of the model after training, a stratified shuffle-split using Scikit-learn has been done to maintain class proportions. 30% of the dataset will be held for evaluation purposes. The data has been loaded into the Keras model using the ImageDataGenerator class. Image data generator is an image augmentation approach that involves applying various transformations to original photos to produce many altered copies of the same image. Depending on the augmentation techniques you use, such as shifting, rotating, flipping, and so on, each copy is unique in some ways. Applying these minor changes to the original image does not affect the target class, but it does provide a new viewpoint on capturing the object in real life. As a result, we frequently employ it to construct deep learning models. These picture augmentation techniques not only increase the amount of your dataset, but also provide a level of variance to it, allowing your model to generalise better on data that hasn't been seen before. When the model is trained on new, slightly modified photos, it also becomes more robust (Manogaran et al., 2020; Rodriguez et al., 2019). The images are maintained at their respective land cover directories. After splitting the dataset, the image augmentations using the generator has been done and also denoted a subset of the training data to be used as validation data during training.

2.3. Machine learning for image classification

The keras ImageDataGenerator has been utilised such that we can obtain the image dataset as a numpy array which can be used by a machine learning model for training and testing. The Random Forest Classifier as been trained for the initial testing. The implementation for machine learning algorithms are based on the two methods Scikit-Lear and Scratch.

2.3.1. Random forest Scikit-learn implementation

Random forest is an ensemble learning-based supervised machine learning algorithm. Ensemble learning is a method of learning in which multiple versions of the same algorithm are combined to form a more efficient prediction model. The random forest algorithm incorporates many similar algorithms.

N random records were selected, and a decision tree was created using these N records.

2.3.2. Random forest implementation from scratch

The dataset is very large in size (21600×12288). We were only able to train the model with Scikit- learn's Random Forest implementation. We can only have a fraction of the training data because the implementation from scratch is inefficient. Even so, it can be seen that it produces fair accuracy when compared to a random guessing approach that gives a 10% accuracy for a 10 class classification problem. And the dataset was qualified, yielding a result accuracy of 61.4%.

3. Proposed methodology

Deep learning models outperform non-deep learning approaches by a significant margin. Initially, the CNN portion of the model will be frozen

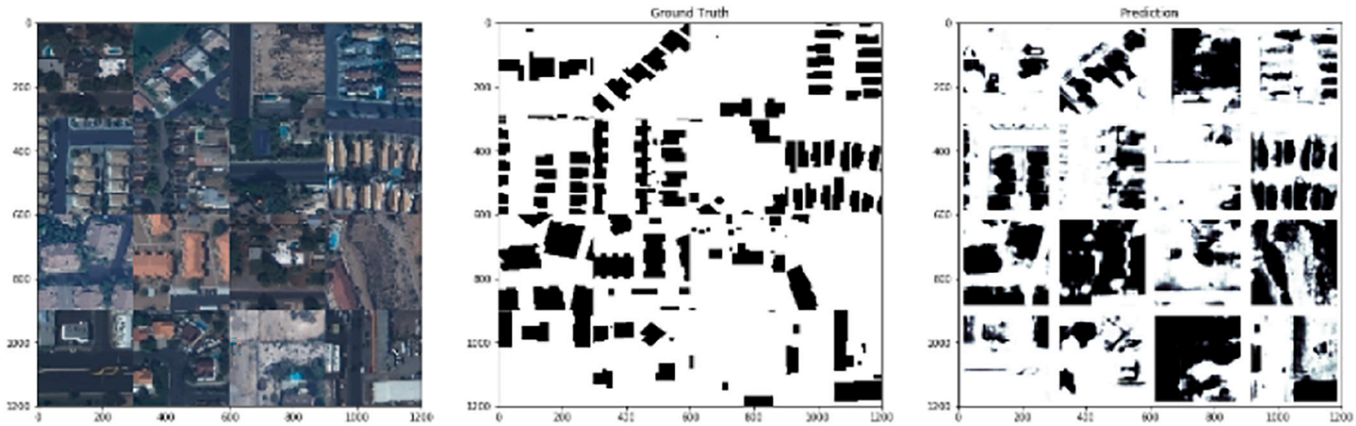

Fig. 11. Land use i) original image, ii) ground truth, iii) prediction.

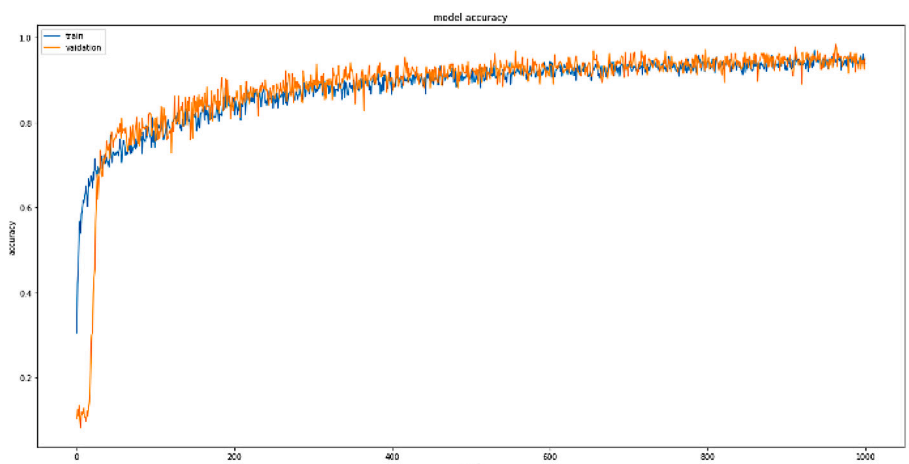

Fig. 12. Modal accuracy of training and testing data.

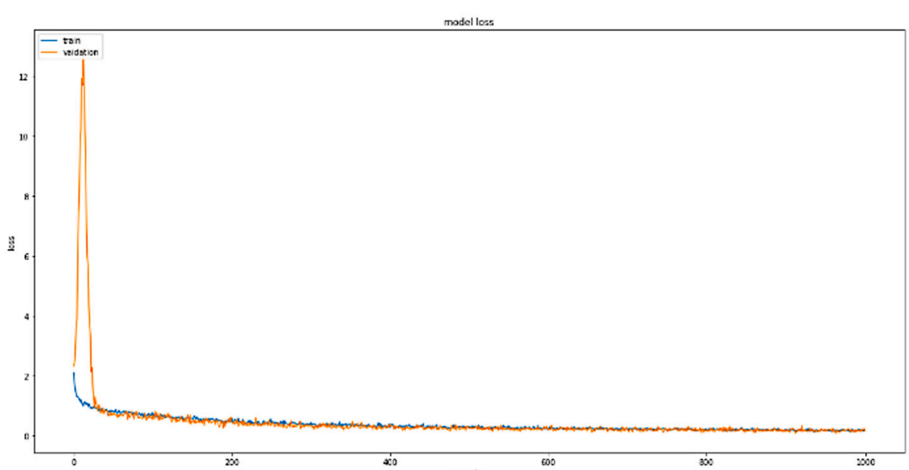

Fig. 13. Modal loss of training and testing data.

with imagenet weights, and dense layers will be trained with a high learning rate of 0.01; later, we will train the entire model end-to-end, fine-tuning with a small learning rate of 0.001 to 0.0001. Using the various categories of ResNet50 and VGG model we will train the algorithm.

3.1. ResNet50

Resnet stands for Residual Network, which is a network that promotes Residual Learning. The number 50 denotes the number of layers. Resnet50 refers to a 50-layer residual network. The model is fed the entire image (64x64x3 = 12,288 pixels) directly. The training data is

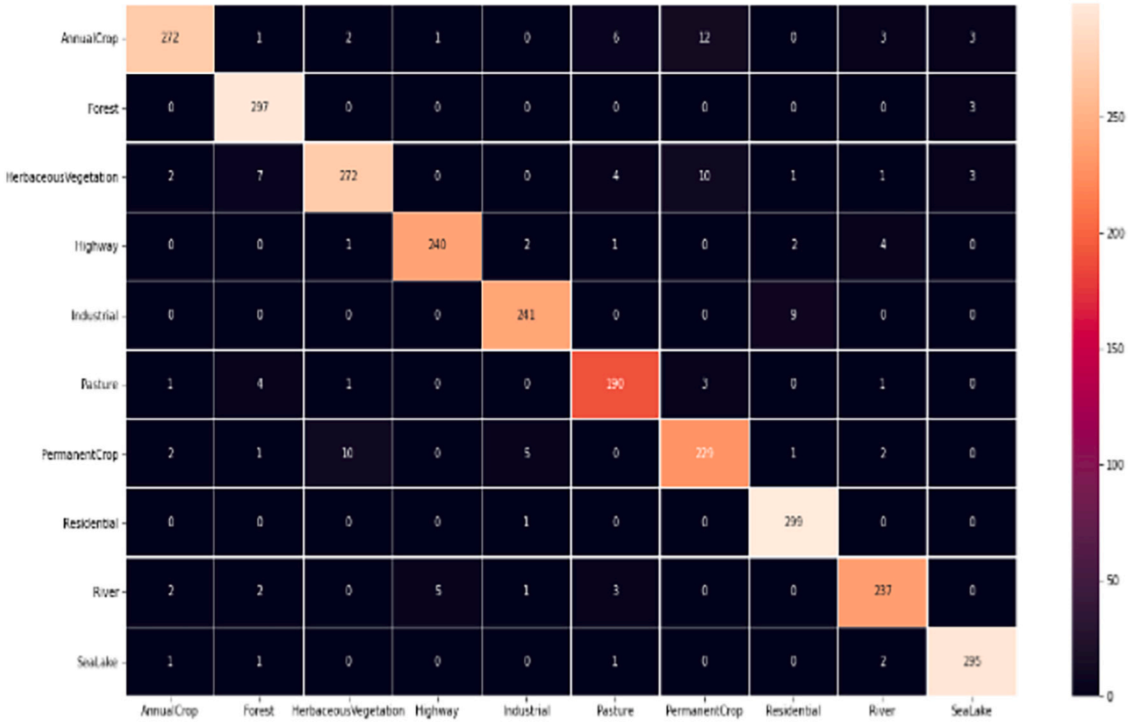

Fig. 14. Confusion matrix for accuracy of prediction.

Table 1
Recall, precision and accuracy value of predicted class.

Class	Recall	Precision	Accuracy	F1 score
Annual crop	0.91	0.97	0.99	0.94
Forest	0.99	0.95	0.99	0.97
Herbaceous vegetation	0.91	0.95	0.98	0.93
Highway	0.96	0.98	0.99	0.97
Industrial	0.96	0.96	0.99	0.96
Pasture	0.95	0.93	0.99	0.94
Permanent crop	0.92	0.9	0.98	0.91
Residential	1.0	0.96	0.99	0.98
River	0.95	0.95	0.99	0.95
Sea Lake	0.98	0.97	0.99	0.98

21,600 and the test data is 5400 from our 80–20 split on the 27,000 samples dataset. The Many layers are stacked and trained to the task at hand in a general deep convolutional neural network. Residual can be clearly described as the subtraction of a function learned from a layer's input. Shortcut connections (directly connecting the input of the nth layer to the input of some (n + x)th layer) are used by ResNet to accomplish this. We will replace the pre-trained ResNet50 model's last predicting layer with our own predicting layers to perform Transfer learning.Weights of the ResNet50 pre-trained model are utilised as feature extractors. The weights of the pre-trained model are frozen and are not changed throughout the training. The dataset has been trained using this method and the trained data has been transferred to the HEVGG19 method.

3.2. HEVGG19

The proposed approach will use the VGG-19 Deep Convolutional Network with the hot encoding process with the pretrained data provided by the RestNet50 using the Transfer Learning system to implement multiclass image classification. The model is fed the entire image (64x64x3 = 12,288 pixels) directly. The training data is 21,600 and the test data is 5400 from our 80–20 split on the 27,000 samples dataset. The VGG19 architecture had 16 layers of CNNs, three fully connected layers, and a final layer for the softmax function; the fully connected layers and final layer would be the same in all network architectures. Many machine learning algorithms are unable to operate directly with categorical data. The divisions must be numerically translated.

This is required for both categorical input and output variables. Since we have ten classes and can expect the shape (Zhang et al., 2020) of y train, y val, and y test to change from 1 to 10, we need to do one hot encoding.

To learn a probability-like number for each potential label value, we'd like to give the network more expressive power. This will assist in making the issue easier to model for the network. A single hot encoding for the output variable can provide a more complex collection of predictions than a single mark.

The image data augmentation will be done here. This is a method for the size of a training dataset by making updated versions of the images in it. We'll start by defining individual ImageDataGenerator instances for augmentation, then match them to each of the training, test, and validation datasets. In this process, we'll use the learning rate annealer. If the error rate does not improve after a certain number of epochs, the learning rate annealer reduces the learning rate. This method will be used to test the validation accuracy, and if it appears to have reached a plateau after three epochs, the learning rate will be reduced by 0.01.

Using the test data set, we can make image class predictions using this model. Finally, we will use confusion matrices to visualise the classification performance on test data. Using the non-normalized confusion matrix, we'll see the same number of correct and incorrect classifications, and then using the normalized confusion matrix, we will see the same in percentages. The model achieves an accuracy score of 98.5% in average.

4. Land cover changes

The historical images of Chennai, Coimbatore and some other regions has been collected from google earth. The dataset contains the historical images of more than 20 years. Using the dataset the prediction and classification of land cover changes has been achieved with an accuracy of 98%. The predict per pixel semantic labelling using the evaluation metric IoU Intersection over Union method. The term IOU (Intersection over Union) is used to indicate the amount to which two boxes overlap. The bigger the overlap region, the higher the IOU. IOU is mostly utilised in object detection applications, where we train a model to generate a box that exactly fits around an item. In land cover we can find some overlap between the various features like building and tree. Moving vehicle and static car. For solving the issue IoU is used.

The dataset has been labelled densely with 8 classes. The image rotation has been done with 3840 × 2160. The different classes has been listed below 1) building (garages, living houses, high raise buildings, security booths, industrial buildings and buildings under construction. 2)Road: includes highway roads, streets, bridges. Excluding Parking lots. 3) Tree: huge trees that have main trunks and canopy. 4) Low vegetation: bushes, grass and shrubs.5) Static vehicles: cars, buses, tankers etc. which are not moving. Excluding - Bicycles and motorcycles. 6) Moving Vehicles: moving cars, buses, tankers etc. Excluding - Bicycles and motorcycles. 7) Human: bikers, pedestrians and other humans doing different activities. 8)Clutter: other objects and activities which are not listed above. Most of the pixels are from classes like tree, building, clutter, low vegetation and road. Fewer pixels are from static car and moving car classes, are less than 1.5%. For human class is 0.2% which is almost zero due to the size.

In Fig. 6, we classify the images based on the eight different classed as mentioned. The image has been segmented based on the color classes and values has been displayed based on the class in Fig. 7. (See Figs. 1–5.)

4.1. Data preparation

The three channel RGB color image has been converted using these helper functions to the single channel label index image. Using the images provided we can able to extract the values of classes from the segment mask. The augmentation and pre-processing transformation has been applied. The Helper functions is used to make the visualization. The images has been resized to 576*1024 to keep the ratio of 9:16.

In the Augmentation process we use Horizontal flip process, Random, Brightness Contrast, CLAHE, Hue Saturation, *IAA Additive Gaussian Noise* with 0.2 probability. For obtaining better results we can also crop the image to1280*720. The overlapping images has been removed.

4.2. Model creation

In the land cover change process, we use the FPN – Feature Pyramid Network model with the efficient Net B3 encoder has been used which gives more accuracy. Feature Pyramid network uses a top-down route and lateral connections to integrate low-resolution, semantically strong features with high-resolution, semantically weak ones. This feature pyramid is created fast from a single input image scale and has extensive semantics at all levels, without losing representational power, speed, or memory. This technique is also used by some concurrent activities, such as DSSD. Mixed precision for the typical data used for Selecting optimization level. For setting the process BCE and Dice Loss with 0.5 contribution with a lookahead optimizer which improves the stability and lowers the variance. The Reduce LR On Plateau with patience 3 and factor 0.3. And on encoder the Initial learning rate is set to 1e-3, and 1e-4.

The PyTorch catalyst framework helps with reproducibility, fast investigation. To track metrics, save hyper-parameters, gradients and model checkpoints the W and b Logger has been used. In Fig. 8, segmentation of each classes are shown. Building, road, static car, tree, vegetation, human, moving car. Each feature has been extracted and shown in the figure with masking layers. The twenty years historical images of some specific locations have been tested. And the class values has been obtained from the historical images and the he values has been gathered and stored as a textual data. Using the textual data the land cover changes has been identified. And the historical textual data and the segmented values has been used to the proposed hevgg algorithm and the prediction of land cover has been obtained with an accuracy of 98%. In the land cover the changes will be in the reduction of trees and vegetation and increase in the values of buildings and roads.

Fig. 9 shows the historical image of a location in Chennai from the time period 2001 to 2020. And Fig. 10 shows the change in land cover using the data obtained from Fig. 9. The images clearly shows that the increase in the size of the building and decreases in the number of trees and lower vegetation. And due to the increase in the building the road size also got increased and transportation also got increased drastically.

5. Result and analysis

This part of the paper explains the result and output obtained from the proposed model. Fig. 11. contains three parts i) Is the cluster of nine satellite images of different regions which are given as the input for the model. Which is also completed the process of augmentation and one hot encoding. In the next part ii) shows the ground truth segmentation of the buildings which are used to predict the future of the build-up areas.

In Fig. 11-iii the build-up area which are going to be used in the future has been predicted and displayed. Here the predicted region shows that how the existing build-up area as shown in the ground truth image extended based on the pretrained values. It is identified that how the build-up area is expanding based by the series of images based on the timeline for same region.

Fig. 12 shows the modal accuracy of the Training to the Testing data. As the dataset images are divided in to 70:30 ratio. Each image has been trained to the model and tested. The graph shows that when the number of training epoch increased the accuracy was increased gradually. Around two thousand epochs has been trained and getting the accuracy to the average of 98%.

Fig. 13 shows the modal loss of the Training to the Testing data. The graph shows that when the number of training epoch increases the loss reduced. Fig. 14 shows the confusion matrix for each data classes. This states that the model is providing the accurate classification for all the classes with 99% of accuracy. Only Herbaceous.

Vegetation and Permanent Crop some false values.

Table 1 shows the Recall, Precision, Accuracy, F1 Score for each predictive class. Thus, we get the final accuracy value of 98%. Which was more accurate when compared to the other CNN models.

6. Conclusion

The main objective of the proposed research methodology is to build a more accurate land use and land cover model. This model will be very useful to predict the future expansion of the cities. Most of the Government bodies like IMD, Water management, Public welfare departments etc. are facing the issues relevant to the planning of the city. Based on this model a proper expansion can be planned to separate the populations evenly. Then it will be more useful for the industries to plan their new project plants. For mitigating the impact of this climatic change. We can plan the green city with a roof top gardens. Which can reduce the urban het island effect. Our model HEVGG19 provides an accuracy of 98.5%. The model with high accuracy has been tested with the historical datas of Chennai and Coimbatore and other regions of India. Thus this model provides a accurate prediction of the changes in land cover of 98.5%.

7. Motivation and contribution

Urbanization creates a very big impact in the climatic change. Which leads to increase in the temperature drastically. Which leads to a demand in water supply and other resources. Too much of temperature and congestion in urban environments leads to increase in air pollution, carbon dioxide level, getting affected by various disease, stress etc. To mitigate this, concern government need this study to make some population distribution plans and to mitigate the temperature and to control the pollution level. The contribution behind the study is to predict the land use distribution based on the satellite image data. And using the climatic data we can mitigate the change in climate. And to understand how the cities got developed and how the vegetation and water bodies got reduced, the land cover change and the prediction is very useful.

Declaration of Competing Interest

None.

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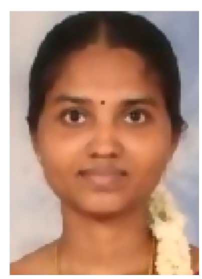

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