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A NOVEL TRANSFER LEARNING BASED DEEP MODEL FOR LAND CLASSIFICATION

Abstract: - A systematic framework for comprehending the qualities and possibilities of different land portions is provided by land classification, which makes it easier to make well-informed decisions and implement sustainable land management techniques across a range of industries. LULC has numerous significant uses in a variety of fields such as Urban planning, agriculture, natural resource management, environmental assessment, infrastructure development, disaster management, Tourism and recreation, Transportation planning, water resource management, etc. Contemporary trends show deep learning technology has achieved very good results in land classification and thus the land classification has become very attractive prospect for research and development. However, having a stable model in terms of training and testing will be the need of an hour. In this proposed system, we have utilized the high performing deep learning model to address the uncertainty prediction in the model. We have used Bayesian model to tackle the uncertainty prediction in the model. Our proposed system is marginally compromised the training and validation accuracy; However, results have shown that the loss curve generated from training and testing a stable model is substantially important to ensure it's learning rate stability as well as general confidence in real-time production of the deep learning model.

Keywords: Land Use and Land classification (LULC), Deep learning, Stable model, Bayesian model

I. INTRODUCTION

Land classification is essential and crucial part for understanding landscape patterns in any country. It is used for monitoring changes of landscape over time, assessing environmental impacts and degradations, land use planning and usage, planning of disaster managements and supporting sustainable development initiatives. It provides valuable information for executives, , researchers, and other stakeholders involved in land management and conservation efforts. Currently in India, data on land usage is gathered through a nine-category classification system on an annual basis by surveying carried out by the officials under ministry of statistics and Programme implementation. According to available statistics, there is information on 305 million hectares out of a total geographical area of 329 million hectares. This means that about 7% of the land is still not classified under the nine-category classification system used.

On recent years, land classification using deep learning techniques has gained significant attention in the research communities due to its potential applications in agriculture, urban planning, environmental monitoring, and more. Further, recent advancements in land classification using machine learning [9][10][11] and deep learning[12][13][14] have focused on enhancing classification accuracy, efficiency, and scalability, while also addressing challenges related to data availability, model interpretability, and uncertainty quantification. Researchers are integrating data from various sources, like satellite imagery [15], LiDAR (Light Detection and Ranging)[17], and aerial photographs[18][19] to improve land classification accuracy and capture finer-scale spatial patterns. Fusion of heterogeneous data sources allows for more comprehensive characterization of land cover and land use[20][21].

Use of transfer Learning based Pretrained Models[22] and semantic segmentation[30][31] in deep learning proved most viable approach to further increase the training and test based accuracy. In Transfer learning techniques, models pretrained on large-scale datasets (e.g. ImageNet[23][24], COCO[25][26]) are fine-tuned for land scape classification, It gained more popularity due to increasing training and testing accuracy with lesser training time as compared to no-transfer learning based model. Pretrained deep learning models, such as convolutional neural networks (CNNs) like ResNet[27], EfficientNet[28], DENSNET[29], etc., provide feature extraction capabilities that can be leveraged for improved classification accuracy, particularly in data-constrained environments. On the other side, many researchers have also utilized semantic segmentation techniques[32][33][34] to classify each pixel in a input image into predefined land cover or land use categories. This technique enabled detailed mapping of complex landscapes for improvement of accuracy. Deep learning-based semantic segmentation models, such as Fully Convolutional Networks (FCNs)[35] and U-Net[36], have shown promising results in accurately delineating land cover boundaries and capturing spatial heterogeneity.

Based on literature review, we have executed many state-of-art algorithms proposed on transfer learning and segmentation method on the land classification have found following research challenges like Data Quality (overlapping areas) and Quantity (limited satellite images), Spatial and temporal dependencies in the satellite

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images, domain adaptation for Transfer Learning, effective use of discriminative features, Lack of uncertainty quantification, etc. In this research paper, we have tried to proposed a solution which could address some of the above-mentioned issues give below.

Improve the quality and quantity of image data using image augmentation; by incorporating probabilistic models, Bayesian neural networks (BNN) to address the for the quantification of uncertainty associated with image features or predictions for stable learning model. Employing the transfer learning method with fine tuning of hyperparameters in DENSNET201 after noise removal and improving quantification of uncertainty proved much promising for the optimized training and validation accuracy. The proposed system also give better accuracy on the testing data.

Many researchers are successful in achieving the higher accuracies in terms of training the model. However, achieving the stable learning model is the hour of a need. In this paper have tried to achieve higher stability in model in terms of training and testing phase which helps to provide consistent predictions under generalized conditions, which is essential for applications where reliability is paramount. Stable models are less susceptible to small changes or noise in the input data[36]. Addressing uncertainty prediction through BNN helped us to prevent unexpected behavior and ensures the model performs well in real-world scenarios. Ethically, stable model promotes fairness by mitigating biases and ensuring consistent treatment of individuals or groups. So we can claim through this paper that our model is indispensable for achieving reliability, trustworthiness, and effectiveness in decision-making processes, thereby contributing to better outcomes and reduced risk though training time accuracy is not very high as compared to different models.

Our work is organized as follows. First, extensive review of existing methods have been done in the section 2. A proposed novel architecture with modified hyperparameter of DENSNET201 with noise removal and image enhancement method is illustrated in Section 3. Datasets, experiments and results are presented in Section 4. Finally, the paper has been concluded in Section 5.

II. LITERATURE REVIEW

Convolutional Neural Networks (CNNs) have shown remarkable success in LULC, yet challenges persist in achieving optimal accuracy, particularly with limited training data and complex image features. The research community is becoming increasingly interested in the technique of classifying images using deep learning models using satellite imagery. Some work has been described below comprehensively while other methods has been mentioned in the analysis table given in the section 3.

A proposal was made by Mohammed Abbas Kadhim [3] for a better classification of satellite images using CNNs through transfer learning. The pre-training process of the CNN models on satellite image datasets resulted in adapting the features to domain specific ones. During the training phase, specific features unique to the domain were gathered and utilized in the testing phase. Extensive testing was conducted on publicly accessible datasets such as Sentinel and Landsat to evaluate the performance of different CNN models like AlexNet, VGG19, GoogleNet, and Resnet50. The experimental findings highlight the success of the method in achieving greater accuracy in classification compared to standard CNN models. When using Resnet50 for feature extraction, the classification results are more accurate and have lower loss compared to other methods. It can be applied to different datasets. Moreover, there are insights into how transfer learning affects model performance, as well as discussions on potential applications and future research directions. In general, this study adds to the existing body of knowledge in remote sensing and image processing, potentially leading to improved methods for analyzing satellite images that are more accurate and efficient.

Indira Pachón introduced a new method called the Random Forest Data Cube-Based Algorithm (RFDCBA)[4] for classifying land cover in Colombia. This technique uses data cubes to store multi-temporal satellite images, allowing for better classification accuracy by incorporating temporal information. We conducted experiments in Colombia using data from the Sentinel-2 satellite to test the performance of the RFDCBA. The CDCol (Colombian data cube)[4] is a tool for the open data cube initiative, focusing on processing, archiving, and analyzing large-scale earth observation data. After comparing our new method with traditional classification techniques, we have found that our approach is better at accurately categorizing different types of land cover.

In a recent study, a novel technique was introduced for categorizing land cover that can manage large quantities of data gathered from different time periods and diverse locations[5]. By combining deep learning, hierarchical segmentation, and multi-scale information fusion, this method aims to improve efficiency. The rise of high-resolution satellite sensors such as Gaofen-2 (GF-2)[5][48] has led to a growing need for precise and effective land cover classification methods. This research paper introduces a comprehensive framework for land cover classification specifically designed for GF-2 satellite images. By utilizing cutting-edge machine learning algorithms, including deep learning approaches, for both feature extraction and classification, the proposed framework has been proven to be effective. The framework was shown to be effective on a wide-ranging dataset that included different geographical regions. The experimental results highlight the accuracy and scalability of the new approach compared to traditional methods, making it useful for various applications such as regional planning and environmental monitoring.

The squeeze and excitation block[6] is a key part of CNNs that boosts feature recalibration by adjusting channel-wise feature responses. The squeeze step condenses spatial details into channel statistics, while the excitation step highlights important channels. This process allows the network to prioritize relevant features and enhance its ability to differentiate between classes. The concept of "concurrent spatial and channel squeeze & excitation" indicates that this improvement works simultaneously on both spatial and channel aspects of the feature maps in FCNs. The recalibration process in AI occurs simultaneously across spatial locations and feature channels, allowing the network to adjust its feature responses based on both spatial and channel contexts. A method combining Channel Squeeze and Spatial Excitation (sSE) block with CNN is introduced in [6]. This approach enhances important features and suppresses strong traits during recalibration. The sSE block is initially recommended for image segmentation. "Multiple convolutional neural networks (CNNs) such as ResNet50, InceptionV3, and VGG19 were utilized in the study. Instead of using softmax on CNN, support vector machine (SVM) and twin support vector machine (TWSVM) were employed as classifiers. CNN was combined with SVM and TWSVM for feature extraction. The experiment results showed that ResNet50 combined with sSE and SVM achieved the most successful outcomes. InceptionV3 also performed well when paired with SVM. Among all classification methods, VGG19 with the sSE block and TWSVM provided the best results.

Urban Land cover classification is the categorization of different types of land cover within urban areas by analyzing satellite or aerial imagery. This process involves identifying and classifying various features present in the urban landscape. Object-based deep learning is commonly used for classifying urban land cover [7]. A research study suggested using a synthetic semivariance function to identify the hyperparameters of superpixel segmentation and fine-tune them to improve the quality of the image's superpixel segmentation output [7]. A convolutional neural network (CNN) and a graph convolutional neural network (GCN) were used to extract detailed features of segments and their spatial relationships. Then, the random forest algorithm was used to classify these segments based on the features obtained. A comparison was made between segment-based and pixel-based classification of urban land cover using Pixel_CNN. The segment-based approach generally had better classification accuracy compared to the pixel-based technique. The new method, incorporating multidimensional features, outperformed traditional approaches commonly used for urban classification.

Many comparative research studies have been conducted to test different architectures and state-of-the-art algorithms on various datasets [8]. It is clearly observable that satellite image classification performs admirably when combined with Deep Learning, thus paving the way for future investigations in this domain using images with varying pixel configurations.

III. PROPOSED MODEL

Our proposed architecture has fusion of image augmentation, noise reduction and image enhancement methods as shown in figure 1.

A. Noise Reduction:

Gaussian smoothing is a widely used technique in image processing and computer vision for reducing noise and blurring images. It employs a 2D convolution operation with a Gaussian kernel, which is a bell-shaped function representing the probability density of a Gaussian distribution. The Gaussian kernel is characterized by two parameters: the standard deviation (σ) and the size of the kernel (usually represented by a matrix size). The standard deviation determines the spread or width of the Gaussian function, while the size of the kernel determines the extent of the smoothing effect.

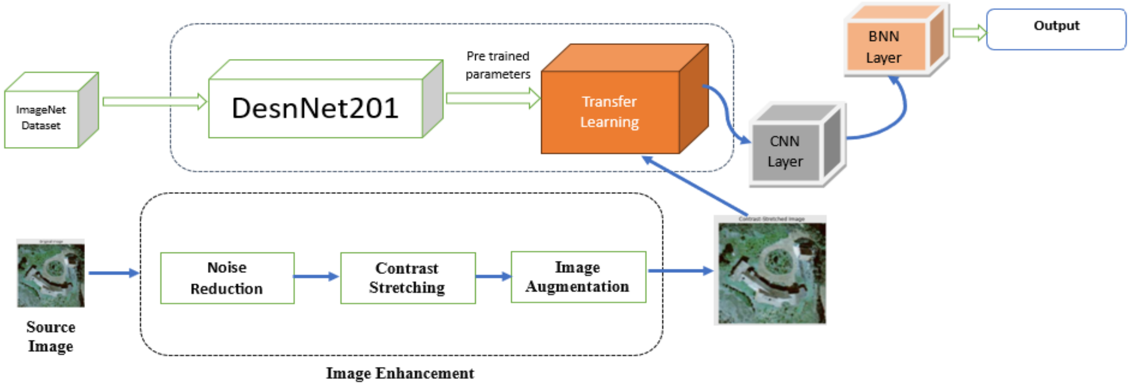


Figure 1 Proposed Bayesian DenseNet model for stable learning

B. Contrast Stretching for image enhancement:

Contrast Stretching method is used to expand the range of pixel intensity values in the input image of land, It will use to improve its contrast and visual appearance. This method enhances the difference in brightness between the darkest and lightest areas of an satellite image, making it more visually appealing and easier to analyze. We have applied Contrast Stretching Transformation technique, a linear transformation to map the original pixel intensities to the desired intensity range. This transformation stretches or expands the pixel intensity values while preserving the relative differences between them.

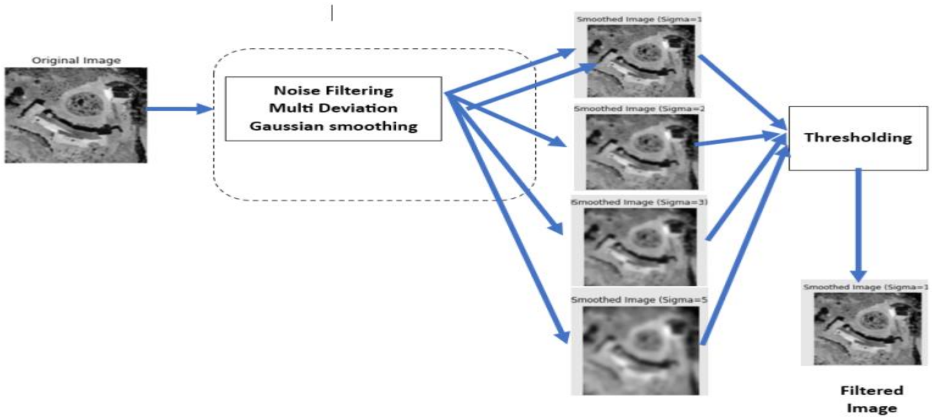


Figure 2 Image enhancement

$$\mathrm{I_{out}(x,y)} = \mathrm{clip}(\mathrm{max_{in}} - \mathrm{min_{in}} * \mathrm{I_{in}(x,y)} - \mathrm{min_{in}} * (\mathrm{max_{out}} - \mathrm{min_{out}}) + \mathrm{min_{out}}, 0{,}255) \quad (1)$$

Where, $\mathrm{min_{in}}$ and $\mathrm{max_{in}}$ are the minimum and maximum pixel intensities in the original image respectively. $\mathrm{min_{out}}$ and $\mathrm{max_{out}}$ are the minimum and maximum pixel intensities in the desired intensity range (usually 0 and 255 for 8-bit images) respectively. clip() is a function that clips the pixel intensity values to ensure they fall within the valid range (0 to 255 for 8-bit images).

C. Bayesian Dense Model:

Bayesian neural networks (BNNs) proved to be a powerful framework for quantifying uncertainty in deep learning models. BNNs provide probabilistic predictions that capture uncertainty inherent in the data and model parameters. Bayesian neural networks treat model parameters as random variables with prior distributions. In the proposed system, Bayesian inference techniques, variational inference methods has been used to approximate the posterior distribution over model parameters given the training data during training time. Description of Bayesian Dense Layer is given here. The output of the Bayesian dense layer can be represent as;

$$Y = ReLU(Z.W + b) \qquad (2)$$

Here, Y is the output of the Bayesian Dense layer, W denote the weight matrix of the Baesian Dense layer b denote the bias vector of the Bayesian dense layer Z denote the input features to the Bayesian dense layer, whichis the output of DENSENET model. The output Y is passed to the output layer which is softmax as below;

$$P = Softmax(Y.U + c) \qquad (3)$$

Where, P is the output probability of shape (B, K) where K is the 21 (number of class label), B represents the batch size, U denote the weight matrix of the SoftMax layer. Applying the additional model of BNN there is a compromise in the accuracy of the additional layer. However, as described in the next section, we could able to get stable learning model during both training and testing phase.

DenseNet, which is also referred to as Densely Connected Convolutional Networks, is a specific type of convolutional neural network design that is well-known for its densely connected structure. In DenseNet, every layer is connected to all other layers in a feed-forward way, facilitating the reuse and propagation of features throughout the network. This ultimately results in improved parameter efficiency and gradient flow. In order to optimize the performance of DenseNet for image classification tasks, it is essential to adjust various hyperparameters. These include parameters such as the number of dense layers, the rate at which feature maps increase, the depth of each block, the size of training batches, the learning rate, the choice of optimization algorithm, the strength of regularization, the probability of neuron dropout, the use of data augmentation during training, the strategy for weight initialization, and the number of output classes.

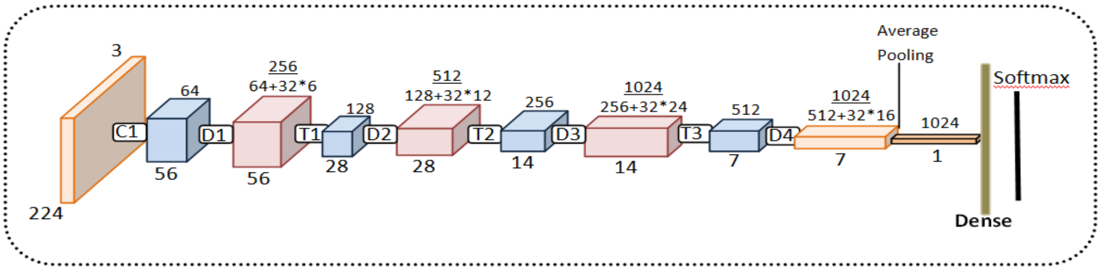


Figure 3 Dense-201. Dx: Dense Block x. Tx: Transition Block x.

Diagram above shows how the input data flows through an initial convolutional layer with number of filters. Dense blocks consist of a series of consecutive convolutional layers (aided by batch normalization and activation functions). Every layer in the dense block receives input from all preceding layers. Transition layers are placed between dense blocks to shrink the spatial dimensions of the feature maps using pooling methods (such as average pooling). The process concludes with global average pooling to condense the spatial dimensions of the feature maps into a single vector, followed by a fully connected layer for classification. In traditional feed-forward neural networks, the output of one layer is connected to the next layer after applying a combination of operations. This layer typically includes convolution, pooling, batch normalization, and an activation function, which can be represented by the equation 4.

$$\mathrm{y} = \mathrm{f}\,(\mathrm{BN}(\mathrm{g}(\mathrm{conv}(\mathrm{pool}(\mathrm{x}))))) \quad (4)$$

Where, x is the input to the layer (e.g., input image or feature map). conv denotes the convolution operation. pool denotes the pooling operation (e.g., max pooling or average pooling). g represents the optional activation function applied after pooling. BN represents batch normalization operation. f represents the activation function applied after batch normalization. According to the process, the input data is changed step by step with each operation. This leads to the ultimate output being the combined outcome of executing each operation in succession.

In DenseNets, the output features from each layer are mixed with the input features. For example, let $\mathrm{x}(0)$ be the input and $\mathrm{x}(l)$ be the feature map at layer l. Thus, the output of each layer in the DenseNet block can be visualized as equation 5.

$$\mathrm{x}(l) \;=\; \mathrm{H}_l([\mathrm{x}(0), \mathrm{x}(1), \ldots, \mathrm{x}(l-1)]) \quad (5)$$

Where: H_l is the transformation (e.g., a sequence of convolutional layers, batch normalization, and activation function) applied to the concatenated feature maps. $[\mathrm{x}(0), \mathrm{x}(1), \ldots, \mathrm{x}(\mathrm{l}-1)]$ represents the concatenation of all the feature maps up to the current layer.

DenseNets maintain feature concatenation across layers, allowing each layer to access the feature maps of all preceding layers. This helps in reusing features and promoting feature propagation within the network, which can aid in learning representations from data. DenseNets are organized into DenseBlocks, with consistent feature map sizes within each block and varying filter numbers between them. Transition Layers are used to down sample between DenseBlocks, usually including batch normalization, a 1x1 convolution, and a 2x2 pooling layer. This setup aids in feature extraction, while also balancing computational complexity and parameter control in the network.If H_l in a DenseNet produces k feature maps each time, we can generalize the i th layer would be like equation 6 and transition layer would be like equation 7.

$$x(l) \;=\; H_l([x(0), x(1), \ldots, x(l-1)]) \quad (6)$$

$$x(l) = T_l(x(l-1)) \qquad (7)$$

Where, H_l in a DenseBlock is the transformation that generates k feature maps at each step. T_l in a Transition Layer applies down-sampling, typically by a combination of batch normalization, a 1x1 convolution, and a 2x2 pooling layer. During the transition layer, the size of the feature map usually decreases because of pooling. The number of channels in the network may go up or down based on the network's design. This transition is important for cutting down the computational workload and managing the number of parameters in the network.

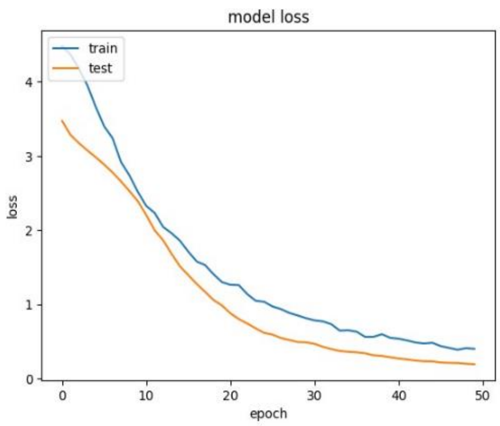
Based on the figure 3, we can see that each layer contributes 32 new feature maps to the existing volume. This explains the increase from 64 to 256 after going through 6 layers. The Transition Block plays a key role in this process by utilizing 1x1 convolutions with 128 filters, followed by a 2x2 pooling with a stride of 2. This leads to a reduction in both the size of the volume and the number of feature maps by half. From analyzing this pattern, we can deduce that the volume in a Dense Block stays the same, while both the volume and feature maps are cut in half following each Transition Block.

IV. Experimental setup and result analysis

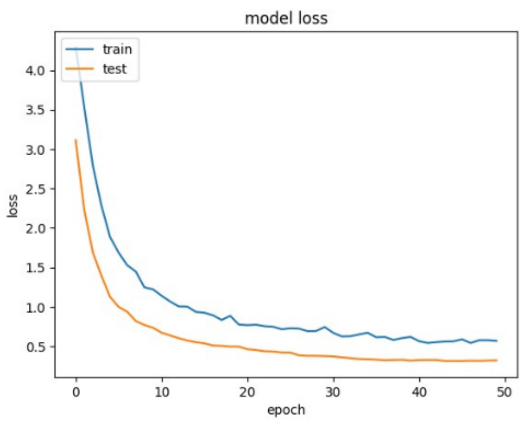
In the experiments, we have used the UC Merced Land Use Dataset consists of 21 classes of land use and land cover, including residential areas, agricultural fields, forests, highways, rivers, and more. Our main purpose in the land classification is to achieve the stable model over the state-of-the art deep learning models. As shown in table accuracy of BNN based model is not higher than the other state-of-the art model. However, proposed model could able to achieve the stable learning after applying the BNN. As shown in table 1 we have executed the state-of-the art models like DENSENET201, VGG16, RESNET50 and proposed BNN based DENSENET201 over 50 epochs with different rate of learning rate. Here, DENSENET201 with learning rate of 0.0003 out performs all other model on land classification data. So, we have chosen that model for proposing the stable learning model. Here, we have made the comparative analysis of our model with the learning rate of 0.0003.

Table 1 Comparison of state-of-the art methods with 50 epochs on different learning rate.

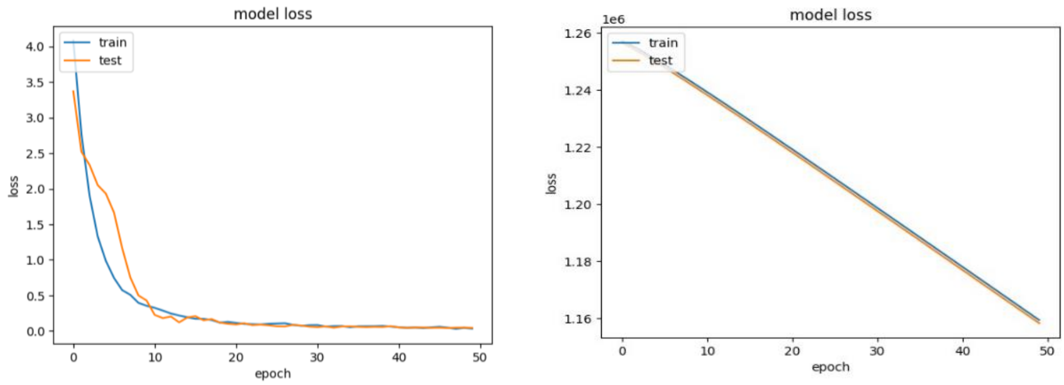
Model	**Learning Rate**	**Training Accuracy**	**Validation Accuracy**
DENSENET201	0.0001	0.78	0.85
	0.0002	0.99	0.98
	0.0003	**0.99**	**0.98**
	0.0005	0.95	0.98
VGG16	0.0001	0.89	0.92
	0.0002	0.95	0.95
	0.0003	**0.95**	**0.94**
	0.0005	0.96	0.96
RESNET50	0.0001	0.94	0.96
	0.0002	0.97	0.97
	0.0003	**0.76**	**0.87**
	0.0005	0.82	0.91
BNN Based DENSENET201 (Proposed)	**0.0003**	**0.84**	**0.85**



(a)



(b)



(c) (d)

Figure 4 Loss progress of DENSENET201 (a) , RESNET50 (b), VGG16(c) and BNN Based DENSENET201(d)

As shown in the figure 4, proposed system is able to achieve the linear decreasing losses over the different epochs on the training and testing stages. Consistent reduction in both training and testing losses indicates that the model is learning from the data and improving its stability over time. Linearly decreasing loss implies that the proposed model is not overfitting to the training data. Overfitting occurs when a model learns to memorize the training data rather than capturing underlying patterns, leading to poor performance on unseen data. Linearly decreasing losses indicate that the model is generalizing well to new, unseen data.

V. Conclusion

In this paper, we aimed to investigate the effectiveness of land classification of UC Merced Land Use Dataset. Our results demonstrate the feasibility of using different deep learning model using transfer learning and additional convolutional neural networks (CNNs) for accurate land cover classification. DENSNET201 out performs all other models during the training time. However, stable land classification model is crucial for urban planning, environmental monitoring, and natural resource management. Our research contributes to the development of stable learning methods for land cover mapping, which can aid decision-makers in assessing land use changes, mitigating environmental risks, and promoting sustainable development. Overall, linearly decreasing losses over both the training and testing phases of model development suggest effective learning, generalization, and stability, which are desirable characteristics for machine learning model.

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