



Enhanced LULC Classification Using CNNs with Transfer Learning and Fine-Tuning: A Regional Study

H. N. Mahendra¹, N. M. Basavaraju¹†, P. Ravi², V. Pushpalatha³ and S. Mallikarjunaswamy¹

¹Department of Electronics and Communication Engineering, JSS Academy of Technical Education (Affiliated to Visvesvaraya Technological University, Belagavi), Bengaluru-560060, Karnataka, India

²Department of Information Science and Engineering, Maharaja Institute of Technology, Mysore (Affiliated to Visvesvaraya Technological University, Belagavi), Mandya-571477, Karnataka, India

³Department of Information Science and Engineering, JSS Academy of Technical Education (Affiliated to Visvesvaraya Technological University, Belagavi), Bengaluru-560060, Karnataka, India

†Corresponding author: N. M. Basavaraju; basavarajunm@jssateb.ac.in

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ABSTRACT

In recent days, due to the high population and rapid urbanization, we have faced several problems related to environmental degradation and climate change. Therefore, Land Use Land Cover (LULC) classification is important in providing accurate and timely information about natural and land resources. Traditional methods for the classification of satellite imagery face several challenges due to the complexities and variability of the data. In this paper, we propose a novel approach to enhance LULC classification using deep learning-based convolutional neural networks with the extraction of features, transfer learning, and fine-tuning. The proposed work first designs convolutional neural networks from scratch to capture spatial features from multispectral resolution satellite imagery covering the study area of Mysuru taluk, Karnataka State, India. Transfer learning is then applied to adapt the pre-trained CNN model to the LULC classification. Furthermore, fine-tuning is employed to fine-tune the adapted CNN model on the target dataset, enabling the model to learn domain-specific features and improve classification performance. The proposed deep learning model performance is demonstrated through experiments on multispectral datasets, where convolutional neural networks, transfer learning, and fine-tuning models provide classification accuracy of 90.41%, 92.50%, and 94.37%, respectively.

INTRODUCTION

Monitoring changes in land use and land cover (LULC) is vital for understanding the dynamic interaction between human activities and natural ecosystems. Population growth, agricultural expansion, industrialization, urbanization, and climate variability have significantly altered terrestrial landscapes, resulting in challenges related to food security, biodiversity loss, water scarcity, and environmental sustainability (Alhassan et al. 2020, Mozumder et al. 2025). Timely and accurate mapping of LULC is therefore indispensable for urban planning, sustainable development, disaster management, and policy-making. Remote sensing (RS) has emerged as the most efficient tool for LULC studies because it provides repetitive, synoptic, and multispectral coverage of Earth's surface over extensive areas at varying spatial and temporal scales (Carranza-García et al. 2019, Kumar et al. 2021).

Traditional approaches to LULC classification predominantly rely on machine learning (ML) methods such as Maximum Likelihood Classification (MLC), k-Nearest Neighbor (k-NN), Decision Trees (DT), Random Forests (RF), and Support Vector Machines (SVM) (Mahendra et al. 2023a). These classifiers have been widely applied in remote sensing tasks due to their computational efficiency and robust mathematical foundation. However, their performance is constrained

by their dependence on hand-crafted spectral, spatial, or textural features that must be manually engineered before classification. Such dependency leads to high subjectivity and model bias, while also requiring domain-specific expertise for feature extraction (Balarabe et al. 2021, Ganesha Raj et al. 2021). Furthermore, ML classifiers often fail to achieve high accuracy in heterogeneous landscapes where spectral overlap, high intra-class variability, and mixed pixels are common problems that are especially prominent in medium-resolution imagery. These limitations underscore the need for more flexible and data-driven approaches that can automatically discover representative features from raw imagery (Kumar et al. 2021, Mahendra et al. 2023b).

Recent developments in deep learning (DL) have revolutionized computer vision and have shown tremendous promise in the field of remote sensing. Convolutional Neural Networks (CNNs), in particular, have demonstrated their capacity to learn hierarchical spectral–spatial representations from imagery, thereby eliminating the need for handcrafted features. By automatically capturing low-level edge features, mid-level textures, and high-level semantic patterns, CNNs offer a significant advantage in classifying complex and heterogeneous land cover categories (Maggiori et al. 2017, Li et al. 2020). Their ability to generalize across spectral bands, spatial resolutions, and contextual patterns makes them especially suitable for LULC mapping RS (Gibril et al. 2016, Geetha et al. 2021).

However, the successful training of CNNs requires very large labeled datasets, which are often unavailable in remote sensing applications (Li et al. 2020). Annotated RS datasets are expensive, time-consuming, and labor-intensive to generate, particularly in developing countries (García-Gutiérrez et al. 2010, Liang et al. 2016). Additionally, training CNNs from scratch demands substantial computational resources and optimized hyperparameter tuning, which can be prohibitive in many practical settings (Li et al. 2020, Naushad et al. 2021). To overcome these challenges, transfer learning (TL) and fine-tuning (FT) strategies have gained significant attention.

Transfer learning leverages knowledge from pre-trained CNN models developed on large-scale datasets such as ImageNet, enabling re-use of learned filters for new but related tasks in RS (Dewangkoro et al. 2021, Häufel et al. 2018). The generic edge and texture features from early CNN layers remain useful across domains, reducing the need for large labeled datasets. Fine-tuning goes one step further by retraining the deeper network layers to adapt to domain-specific characteristics of RS data, ensuring improved generalization and accuracy (Naushad et al. 2021, Shabbir et al. 2021). Such approaches strike a

balance between computational feasibility and classification performance, making them highly relevant for RS-based LULC applications.

The efficiency of TL and FT has been demonstrated across multiple RS domains, including urban expansion monitoring, vegetation type classification, crop yield estimation, and disaster damage assessment. Studies have reported that CNN-based TL models consistently outperform traditional classifiers and even outperform CNNs trained from scratch in limited-data scenarios. Moreover, advanced CNN architectures such as VGGNet, ResNet, DenseNet, and EfficientNet have introduced innovative scaling mechanisms that improve accuracy while reducing computational complexity. Among these, EfficientNet stands out due to its compound scaling approach, which balances network depth, width, and input resolution, making it highly suitable for large and medium-scale RS applications (Maggiori et al. 2017, Mahendra et al. 2025, Mahendra & Mallikarjunaswamy 2023).

Despite this progress, a notable research gap persists: most DL studies in RS prioritize high-resolution imagery such as Sentinel-2 (10 m) and Landsat-8 (30 m), while medium-resolution imagery from the LISS-III sensor (23.5 m) remains largely underexplored. LISS-III provides cost-effective, regionally relevant data that is widely utilized in India for agricultural monitoring, forest assessment, hydrology, and urban planning. However, applications of advanced CNN-based DL methods to LISS-III imagery are still limited, with existing studies focusing more on conventional ML techniques or unsupervised classification approaches (Pushpalatha et al. 2024). This underrepresentation is striking, given the operational importance of LISS-III in India's remote sensing programs and its widespread use for regional-scale resource management.

Motivated by this gap, the present study undertakes a systematic exploration of DL strategies for LULC classification using IRS LISS-III imagery of Mysuru Taluk, Karnataka, India. Specifically, we investigate and compare three CNN-based strategies. The choice of EfficientNetB7 is motivated by its demonstrated efficiency in balancing accuracy with computational demands, making it a strong candidate for medium-resolution RS applications.

To ensure a comprehensive evaluation, we also benchmark these DL models against traditional ML classifiers such as SVM, RF, DT, k-NN, and MLC using the same LISS-III dataset. Our study ensures a fair and controlled comparison by applying all models to the same dataset under identical conditions. This approach not only strengthens the credibility of performance assessment but also provides practical insights into the suitability of different

classifiers for medium-resolution RS applications. The key contributions of this study include:

1. We employ the region-specific LISS-III dataset of Mysuru Taluk, Karnataka, which is relatively underexplored in deep learning-based LULC studies, thereby providing insights into a critical region experiencing rapid land-use transitions.
2. We adapt and fine-tune the EfficientNetB7 architecture for multi-class LULC classification, redesigning the dense layer to suit regional data.
3. We present a direct performance comparison between a CNN designed from scratch and transfer learning models, highlighting their trade-offs under limited data availability.

Finally, the outcomes of this study are positioned within the framework of sustainable development and regional planning, emphasizing the applied significance of our findings beyond methodological comparisons.

Objectives

The primary goal of this study is to improve LULC classification accuracy. To accomplish this goal, the research has delineated the following objectives:

1. To design CNNs from scratch to extract high-level features from satellite imagery for LULC classification.
2. To apply the transfer learning DL model to improve the performance of LULC classification.
3. To further enhance the classification accuracy and optimize model performance through the process of fine-tuning the DL model.

Related Works

In the literature, several researchers explored the use of deep learning techniques, including CNN, transfer learning, and fine-tuning, to enhance LULC classification. Weng et al. (2017) proposed a method that combines CNN and ELM to improve classification performance. Zhu et al. (2020) focused on the high-resolution satellite image classification for land cover classes with a high total accuracy of 89.6% through the use of an improved SMOTE algorithm for sample augmentation. Douass et al. (2022) applied a transfer learning approach, retraining a pre-trained Resnet18 model to classify aerial images of the Tangier region. Alem et al. (2020, 2021) provided a comprehensive review of methods in deep learning for the classification of LULC, highlighting the use of CNN models in this field.

Agarwal et al. (2022) proposed an innovative approach to LULC classification by using satellite imagery and deep

learning techniques. This method utilizes high-resolution satellite images to automatically extract the optimal feature for land cover classification. Similarly, Xia et al. (2022) developed a deep learning model specifically designed for LULC classification, employing a seven-layer CNN to achieve effective results. Uba (2019) also explored the use of techniques of deep learning for LULC classification, demonstrating how these algorithms can effectively process very high spatial resolution images to automate LULC identification. In another study, Kalantar et al. (2022) presented a deep ensemble learning framework for LULC classification using hyperspectral PRISMA imagery, focusing on extracting critical information to enhance classification accuracy.

Nijhawan et al. (2019) introduced a forward-looking framework of deep learning for the classification of LULC using remote sensing data, and provided better performance as compared to existing methods. Similarly, Song et al. (2019) presented a novel approach utilizing a 1D CNN for the classification of LULC in satellite images, where the application of the CNN to each pixel in the spectral domain significantly improved classification accuracy. Liu et al. (2020) proposed a LULC classification method that integrates CNN with a digital surface model and remote sensing data, achieving an impressive overall accuracy of 95.57%. Yang et al. (2019) developed a CNN-based approach for LULC classification, where the inclusion of an infrared band and data provided better classification results compared to traditional RGB images.

Yang et al. (2021) introduced a deep-learning framework for the consistent classification of land-use objects within geospatial databases. This approach is based on CNNs to predict land use across multiple hierarchical levels simultaneously and demonstrates superior performance compared to existing methods. Kussul et al. (2017) developed a model of deep learning for classifying crop and land cover types using satellite data. This architecture, utilizing an ensemble of CNNs, significantly outperformed models based on MLPs. Patel et al. (2022) proposed a multi-level feature extraction technique for automated land cover classification, integrating LSTM networks and deep CNNs. This model exceeded the performance of benchmark pre-trained CNN models.

Rao et al. (2022) presented an advanced algorithm based on deep learning for classifying LULC using satellite imagery. This approach utilized the DeepLabv3 model, a semantic segmentation framework employing atrous convolution to capture multi-scale contexts. This is achieved by adopting multiple atrous rates in a cascading or parallel manner to accurately determine the scale of land segments.

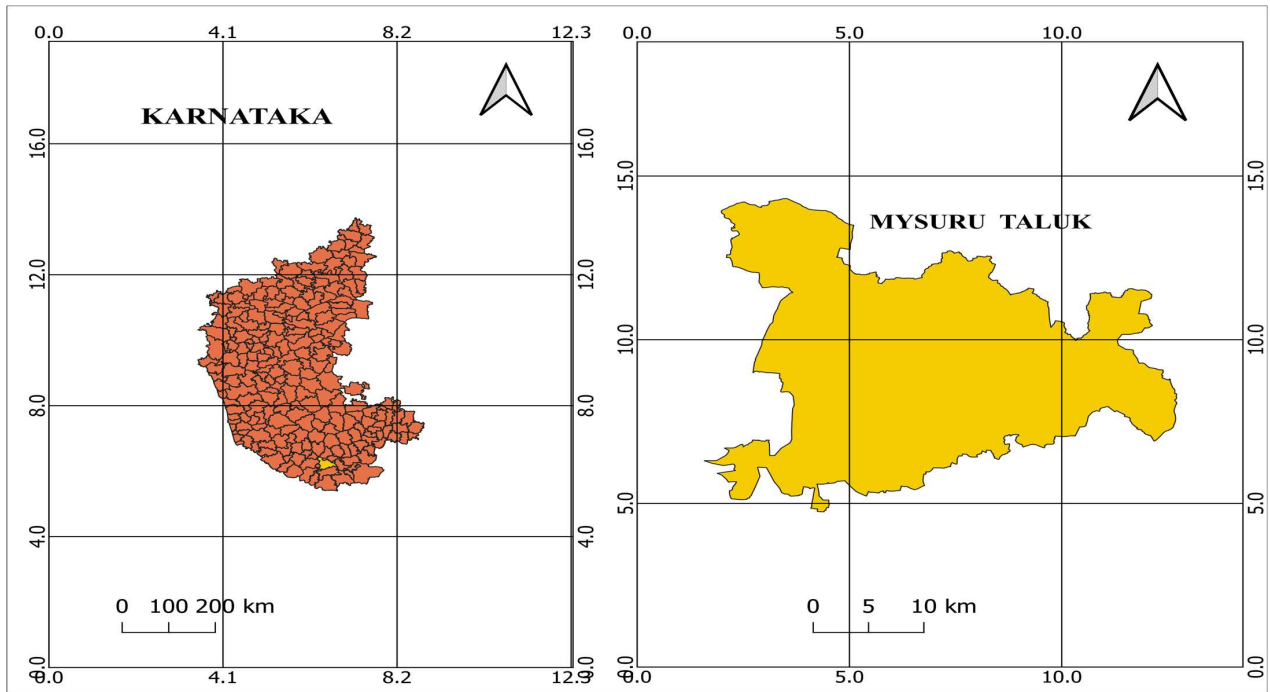


Fig. 1: Study area.

Yang et al. (2019) proposed a highly efficient and accurate deep learning-based method for large-scale land-use mapping, utilizing a deep convolutional neural network to achieve superior results. Bergado et al. (2020) introduced a land-use classification method using deep multitask networks, which outperformed other classifiers by at least 30% in the average F1-score. Fahmi et al. (2022) focused on patch-based land cover classification and demonstrated that ResNet-50 achieved the highest validation accuracy for this task. Weng et al. (2018) developed a CNN-based land-use scene classification model that incorporates a constrained extreme learning machine (CNN-CELM). This model not only enhances generalization capabilities but also reduces training time compared to other state-of-the-art methods. Collectively, these studies highlight the significant potential of deep learning in enhancing the accuracy and efficiency of LULC classification.

MATERIALS AND METHODS

Study Area

In this research, Mysuru taluk in Karnataka, India, is identified as the study area, as shown in Fig. 1. Situated in southern Karnataka, Mysuru taluk is famous for its rich cultural heritage, historical importance, and peaceful landscapes. The taluk features a variety of landscapes, from lush forests to fertile plains, dotted with villages and towns.

As the region's administrative center, Mysuru taluk combines tradition and modernity, with its iconic Mysore Palace standing as a symbol of its royal history. The area attracts tourists interested in its regal architecture and lively festivals, while also being a center of academia, with institutions like the University of Mysore contributing to its intellectual life. Furthermore, the agrarian landscape supports a strong agricultural sector, with crops like sugarcane, paddy, and silk playing key roles in the economy.

Dataset and Tools

In this research work, the Resourcesat-1 satellite, Linear Imaging Self-Scanning Sensor-III (LISS-III) sensor data of the year 2019 covering the Mysuru taluk are downloaded from the ISRO Bhuvan portal and used for modeling the CNN, transfer learning, and fine-tuning. The study area was obtained in six image patches, which were merged and cropped to the exact Mysuru taluk boundary using the QGIS tool. The Resourcesat-1 satellite, equipped with the LISS-III sensor, provides invaluable data for various applications, including land use planning, agriculture, forestry, and environmental monitoring. LISS-III captures images with a 23.5-meter spatial resolution in four spectral bands ranging from visible to near-infrared. This high-resolution data enables detailed analysis of land cover changes, vegetation health, and natural resource management over large areas. Its ability to acquire images in multiple spectral bands supports

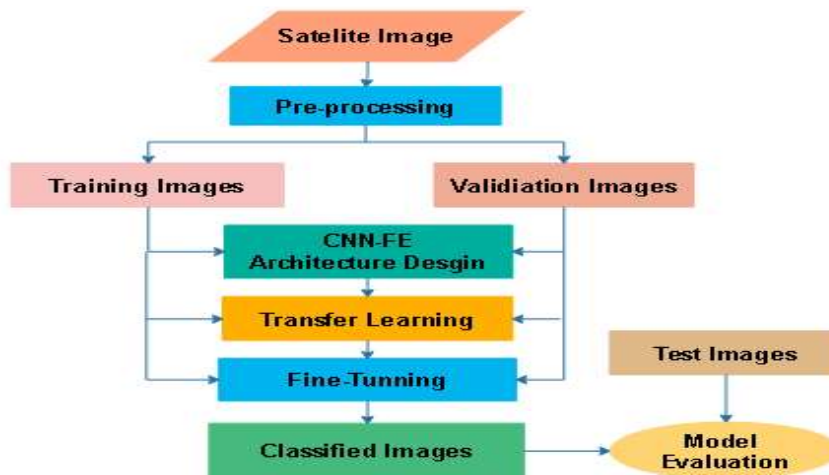


Fig. 2: Methodology followed in the research work.

differentiating land cover types and detecting environmental variations, making Resourcesat-1 LISS-III a vital tool for sustainable development and scientific research.

High-level programming languages like Python are useful for creating DL models. Python is an easy-to-use and adaptable programming language that may be used to build a variety of interactive libraries for many learning and machine learning models. Additional tools that are utilized with Python include MATLAB R2023b, QGIS, and TensorFlow.

Methodology

The proposed research methodology to improve LULC classification accuracy using models such as CNN-feature extraction (CNN-FE), transfer learning, and fine-tuning is outlined in Fig. 2. Initially, a satellite dataset covering diverse land cover types in Mysuru taluk was collected and preprocessed. The study area was obtained from six image patches, which were merged and cropped to match the Mysuru Taluk boundary using QGIS. Preprocessing included radiometric and geometric corrections, normalization, and augmentation to create a balanced, robust dataset for deep learning training. The dataset was split into 60% training, 20% validation, and 20% testing. As detailed in Table 1, the deep learning hyperparameters were configured for training. After training and validation, model performance was assessed on the test dataset.

A CNN architecture was designed from scratch as a feature extractor to automatically identify discriminative features from raw imagery. This architecture captures spatial dependencies and hierarchical data representations effectively. Transfer learning was applied using pre-trained EfficientNet models, leveraging their prior knowledge to accelerate learning and enhance adaptation to the LULC classification task.

Fine-tuning involved adjusting the pre-trained EfficientNet weights on the target dataset through backpropagation, allowing the model to refine its features for improved classification. Regularization and hyperparameter tuning techniques were employed to enhance the model's generalization to unseen data.

Finally, model evaluation was conducted using metrics such as overall accuracy, precision, recall, and F1-score on the test dataset. The proposed deep learning approach was compared with existing methods to evaluate its effectiveness. Sensitivity analysis was performed to assess robustness to data and parameter variations. This comprehensive evaluation highlights the strengths and limitations of the methodology, guiding future improvements and applications in land use analysis and remote sensing.

Proposed Deep Learning Methods

Convolutional Neural Networks-Feature Extraction (CNN-FE)

The proposed CNN architecture begins by preprocessing LISS-III satellite data, involving downloading, merging, cropping, and resizing images to a standardized 224x224x3 format. The model's input layer is configured to accept

Table 1: Hyperparameters are used to train the model.

Hyperparameters	Values
Dropout	0.25
Loss Function	Cross-entropy
Activation Function	ReLU, Sofine-tuning max
Epochs	100
Batch Size	64
Optimizers	Adam
Learning rate	0.001

images of this size. The architecture comprises eight convolutional layers, each utilizing various filter sizes to extract diverse features, enhancing multi-scale feature detection. This approach improves the network's ability to identify fine details and complex patterns within satellite imagery, as illustrated in Fig. 3.

The first convolutional layer uses 32 filters of size 1x1 with a stride of 1, enabling pixel-by-pixel traversal across the input image. With no padding, the spatial dimensions of the output are reduced. Next, a second convolutional layer with 32 filters of size 2x2, stride 1, and no padding is added, allowing for the extraction of slightly more complex spatial features. This sequential stacking facilitates the capture of both fine and broader spatial details.

A third convolutional layer with 64 filters of size 2x2, stride 1, and no padding further refines feature extraction. The fourth layer employs 64 filters of size 3x3, also with stride 1 and no padding, enabling the extraction of more intricate features. These layers collectively bolster the model's capacity to recognize complex patterns within the data. This progressive design aims to refine feature extraction, supporting accurate classification and detection tasks.

As the network deepens, successive convolutional layers extract increasingly complex features. The fifth layer uses 128 filters of size 3x3, the sixth employs 128 filters of size 4x4, both with stride 1 and no padding. The seventh and eighth layers employ 256 filters of sizes 3x3 and 4x4, respectively, with stride 1 and no padding. This layered structure enhances the model's ability to capture detailed information, optimizing features for subsequent classification.

Activation functions are essential for modeling complex data relationships. After each convolutional layer, an activation function, typically ReLU, is applied. ReLU is computationally efficient, producing zero for negative inputs and the input itself for non-negative inputs. Its simplicity accelerates computation and implementation. Importantly, ReLU introduces non-linearity, essential for learning complex patterns, and helps mitigate the vanishing gradient problem in deep networks, improving overall performance in tasks like LULC classification.

Max pooling layers follow each convolutional layer to reduce feature map dimensions, preserving key information while improving computational efficiency. Pooling involves sliding a window across the feature map and selecting the maximum value within each window, aiding in the detection of more complex patterns and objects.

The architecture incorporates eight max-pooling layers, each placed after the convolutional layers and designed with

various kernel sizes and stride values for effective spatial reduction. The first pooling layer uses a 2x2 kernel with a stride of 1, the second employs a 3x3 kernel with a stride of 2. Layers three and four use 3x3 kernels with strides of 2 and 3, respectively. Layers five and six utilize 4x4 and 5x5 kernels with stride 2. Layers seven and eight feature 4x4 and 3x3 kernels with strides of 3 and 5, respectively. This configuration systematically reduces the spatial dimensions of feature maps, ensuring efficient feature extraction.

$$(n_h \cdot f + 1) / s \times (n_w \cdot f + 1) / s \times n_c \quad \dots(1)$$

where,

n_h - height of feature map

n_w - width of feature map

n_c - channel numbers

s - stride length

f – filter size

The proposed CNN incorporates batch normalization within its architecture to improve training speed, stability, and overall performance. This layer normalizes inputs by scaling activations, maintaining a consistent feature distribution. By reducing internal covariate shift, batch normalization lessens sensitivity to weight initialization and learning rates, promoting stable training. It also diminishes the reliance on dropout by inherently regularizing the network. Furthermore, batch normalization smooths the loss landscape across mini-batches, enabling faster convergence and better generalization.

Following the convolutional and pooling layers, three fully connected (FC) layers are used to map learned features to the output space. These layers contain 1024, 512, and 4 neurons, respectively. Each neuron in an FC layer is connected to every neuron in the previous layer, allowing the network to capture complex global patterns. This setup transforms feature representations into a structured output, with the final layer's 4 neurons corresponding to the target classes.

In this model, the first FC layer with 1024 neurons extracts a broad set of abstract features from the data. The second FC layer with 512 neurons refines these features by reducing dimensionality. The final FC layer with 4 neurons acts as the output layer for classification purposes. This layered approach ensures a seamless transition from spatial feature extraction by the CNN layers to decision-making, thereby enhancing classification accuracy for the targeted tasks.

The objective function layer, positioned as the final component in a CNN, computes the error, or loss, between the true target values and the model's predictions. Situated after the output layer, this layer employs a specific loss

function, commonly cross-entropy loss for classification tasks, to quantify prediction errors. This error, expressed as a scalar value, indicates how much the model's predictions deviate from the actual outcomes. Incorporating this error into backpropagation, the network adjusts its weights and biases to minimize future errors. Consequently, the objective function layer directs the learning process, helping the network improve its accuracy over time. Cross-entropy loss is especially well-suited for classification tasks, effectively handling multi-class outputs as illustrated in equation (2). Through repeated training cycles, this process enables the network to progressively refine its predictions and enhance overall performance.

$$L_{soft \max loss} = -\frac{1}{N} \sum_{i=1}^N \log \left(\frac{e^{hy_i}}{\sum_{j=1}^C e^{h_j}} \right) \quad \dots(2)$$

$$\text{With } y_i \in \{1, 2, \dots, C\}$$

$$h = \{h_1, h_2, \dots, h_C\} \quad \dots(3)$$

In this notation, y_i represents the true label, C is the total number of classes, and h corresponds to the final output of the architecture.

Transfer Learning Method

Transfer learning is a powerful technique in machine learning that utilizes pre-trained models to enhance the accuracy of Land Use/Land Cover (LULC) classification. This approach is particularly valuable in LULC tasks because it reduces the need for extensive labeled satellite imagery, which is often challenging to obtain. Instead of training a model from

scratch, a deep learning model pre-trained on large datasets like EfficientNet can be fine-tuned for specific LULC applications. This process transfers the learned features from general image recognition to the unique patterns found in satellite or aerial images, such as vegetation, urban infrastructure, and water bodies.

Transfer learning not only cuts down on computational costs and training time but also frequently boosts accuracy, as the model already understands basic visual features like edges, textures, and shapes. Fine-tuning typically involves modifying the weights of the final layers or replacing them with new layers tailored to the LULC task. This method is especially effective when labeled data is limited, as it eliminates the need for large, labeled datasets common in remote sensing. Additionally, transfer learning works well with modern architectures like convolutional neural networks (CNNs) and plays a key role in making LULC classification more efficient.

Fine-Tuning

Fine-tuning for land use land cover (LULC) classification involves customizing a pre-trained deep learning model, typically a convolutional neural network (CNN), to accurately categorize satellite images into specific land cover classes. This process begins with a model pre-trained on extensive datasets, such as EfficientNet, to utilize its existing feature representations. During fine-tuning, only the final layers are trained while the earlier layers are kept fixed, since they capture general features like edges and textures. The satellite data replaces the model's last classification layer with a new

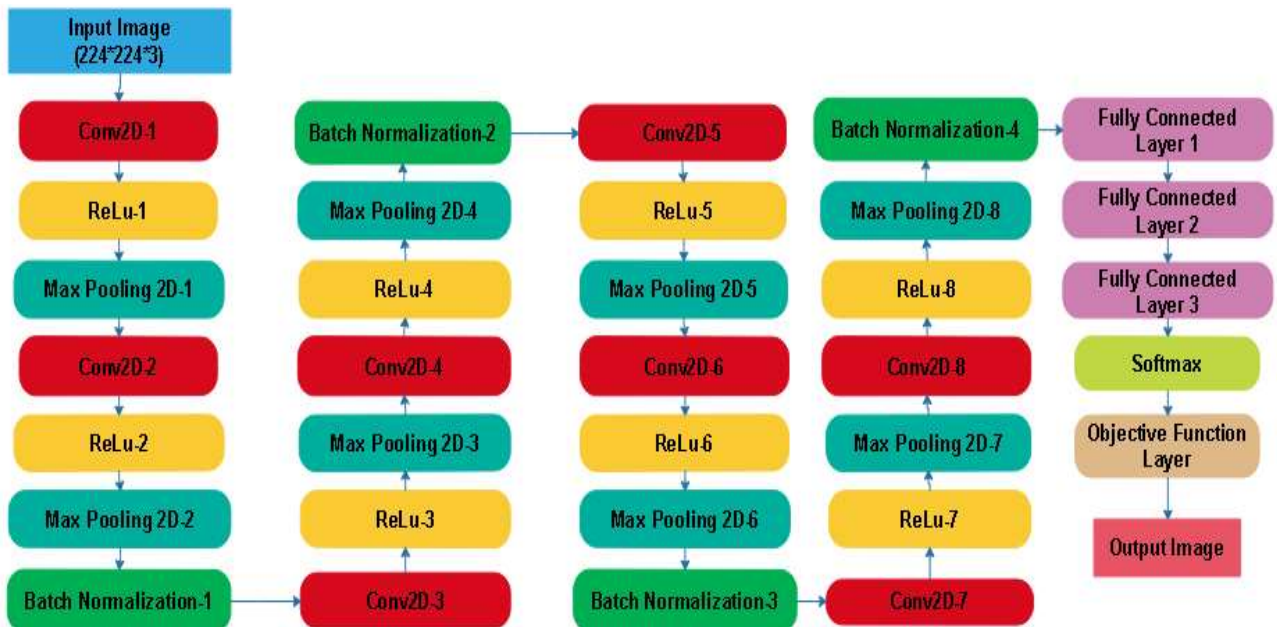


Fig. 3: Proposed CNN architecture.

layer corresponding to the number of LULC classes. The model then learns to distinguish between land cover types such as forests, urban areas, water bodies, and agricultural zones. Key techniques include tuning the learning rates, applying data augmentation, and employing transfer learning to accelerate training. This approach minimizes the need for large datasets and computational power, making it effective for LULC classification while enhancing accuracy. Fine-tuning is particularly crucial when domain-specific patterns differ significantly from those in the original training data.

RESULTS AND DISCUSSION

The experiments were conducted on a laptop computer with an Intel Core i3-6006U CPU running at 2.00GHz and 12 GB of RAM. The MATLAB R2023b and QGIS tools are used with the Python programming language.

Training and Validation

We used a satellite data set of the Mysuru taluk to assess the deep learning models' performance in LULC classification. Training, validation, and test samples make up 20%, 20%, and 60% of the dataset, respectively. In addition, the model is trained and validated using a training and validation dataset, and its performance is evaluated using a test dataset.

We trained and validated the model during experiments using training and validation datasets once the experimental settings were set. Additionally, test data sets were used to assess the model's performance in terms of accuracy, recall, f1-score, and precision using a confusion matrix. The confusion matrix shows how well the class did based on how accurately or poorly the rows and columns in the intersections are classified. The categorical cross-entropy

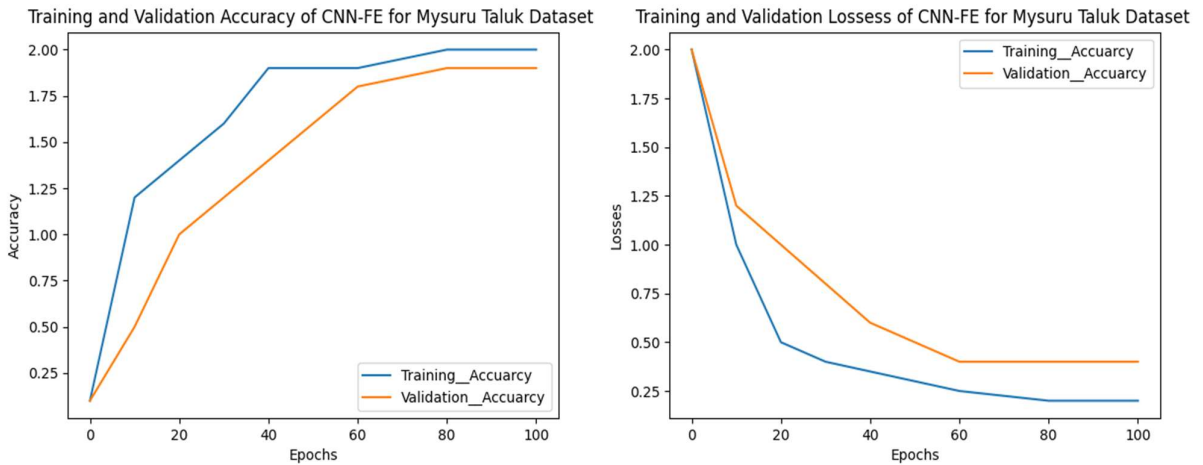


Fig. 4: Training and validation of CNN-FE.

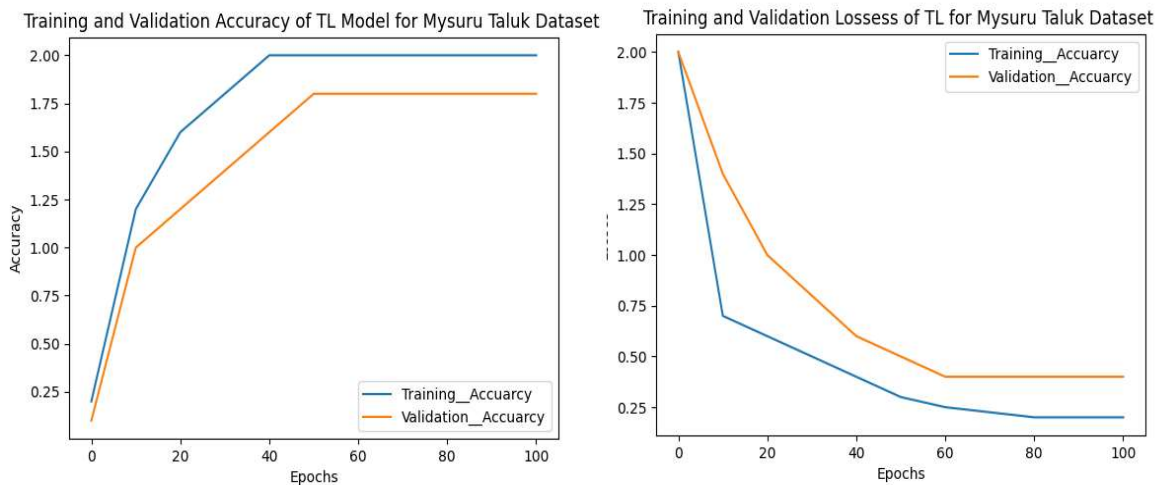


Fig. 5: Training and validation of transfer learning.

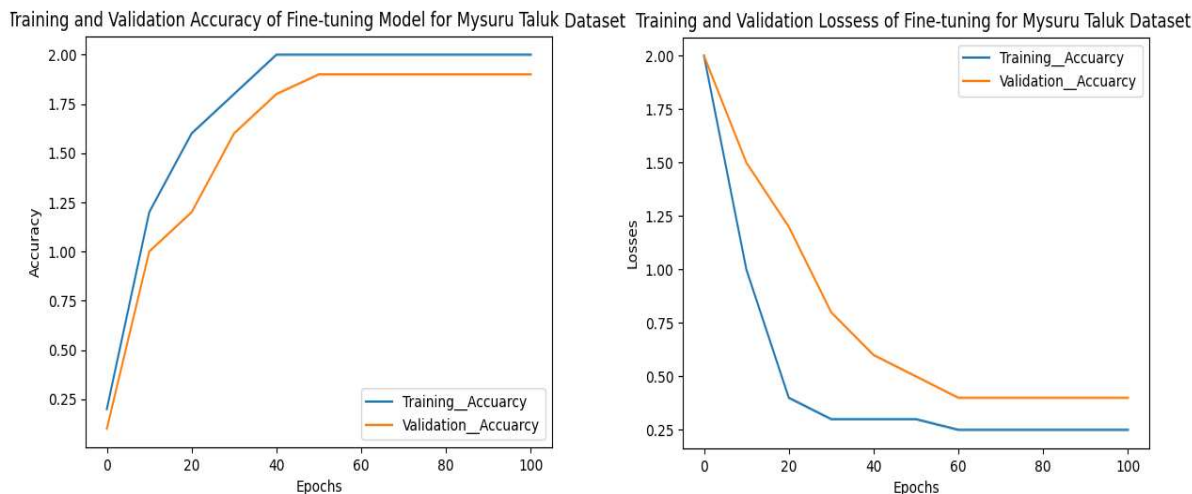


Fig. 6: Training and validation of Fine-tuning.

loss function was used to calculate the accuracy and errors.

The CCN-FE, transfer learning, and fine-tuning model's training and validation accuracy are shown in Fig.4, Fig. 5, and Fig. 6 (on the left), respectively, which is anticipated to increase in epoch increments. Fig. 4, Fig. 5, and Fig. 6 (on the right) show the losses of training and validation of the CCN-FE, transfer learning, and fine-tuning model, respectively, which are anticipated to decrease in epoch increments.

LULC Classification and Assessment

LULC classification was performed using all three trained DL models—CNN-FE, transfer learning, and fine-tuning—on LISS-III sensor data from 2019 for Mysuru Taluk. The classified maps generated by CNN-FE, transfer learning, and fine-tuning are shown in Fig. 7, Fig. 8, and Fig. 9, respectively. Throughout the study area, the main LULC classes include built-up areas, agricultural land, water bodies, forests, and other landscape features. The land area for each class was determined for each of the three classified maps. The area of each land class in square kilometers and its percentage of the total area covered by all classes are listed in Table 2. Mysuru Taluk spans a total area of 797 sq. km. Built-up areas were estimated to cover approximately 200.42

sq. km, or 25.14% of the total area, using the CNN-FE model. Similarly, the transfer learning and fine-tuning models identified built-up areas to cover 202.24 sq. km (25.37%) and 201.69 sq. km (25.30%), respectively. Agricultural land made up the majority of the study area, covering 473.60 sq. km (59.42%) with CNN-FE, 473.06 sq. km (59.36%) with transfer learning, and 474.12 sq. km (59.48%) with the fine-tuning model.

Water bodies were found to cover 36.82 sq. km (4.61%) with CNN-FE, 35.28 sq. km (4.42%) with transfer learning, and 36.35 sq. km (4.56%) with the fine-tuning model. Forested areas accounted for 61.61 sq. km (7.73%) with CNN-FE, 63.15 sq. km (7.92%) with transfer learning, and 62.19 sq. km (7.80%) with the fine-tuning model. Waste land collectively covered 24.55 sq. km (3.08%) with CNN-FE, 23.46 sq. km (2.94%) with transfer learning, and 22.65 sq. km (2.84%) with the fine-tuning model. These results show consistency across the three models in identifying land cover types, with minor differences in area estimates.

Performance Analysis of DL Models

We evaluated the performance of each deep learning (DL) model using 480 test datasets. In addition to accuracy, metrics

Table 2: Mysuru taluk LULC assessment of CNN-FE, transfer learning, and fine-tuning.

Class Name	CNN-FE		Transfer Learning		Fine-tuning	
	Area [in Sq. km]	% Area	Area [in sq. km]	% Area	Area [in Sq. km]	% Area
Built-up	200.42	25.14	202.24	25.37	201.69	25.30
Agriculture land	473.60	59.42	473.06	59.36	474.12	59.48
Water bodies	36.82	4.61	35.28	4.42	36.35	4.56
Forest	61.61	7.73	63.15	7.92	62.19	7.80
Waste land	24.55	3.08	23.46	2.94	22.65	2.84

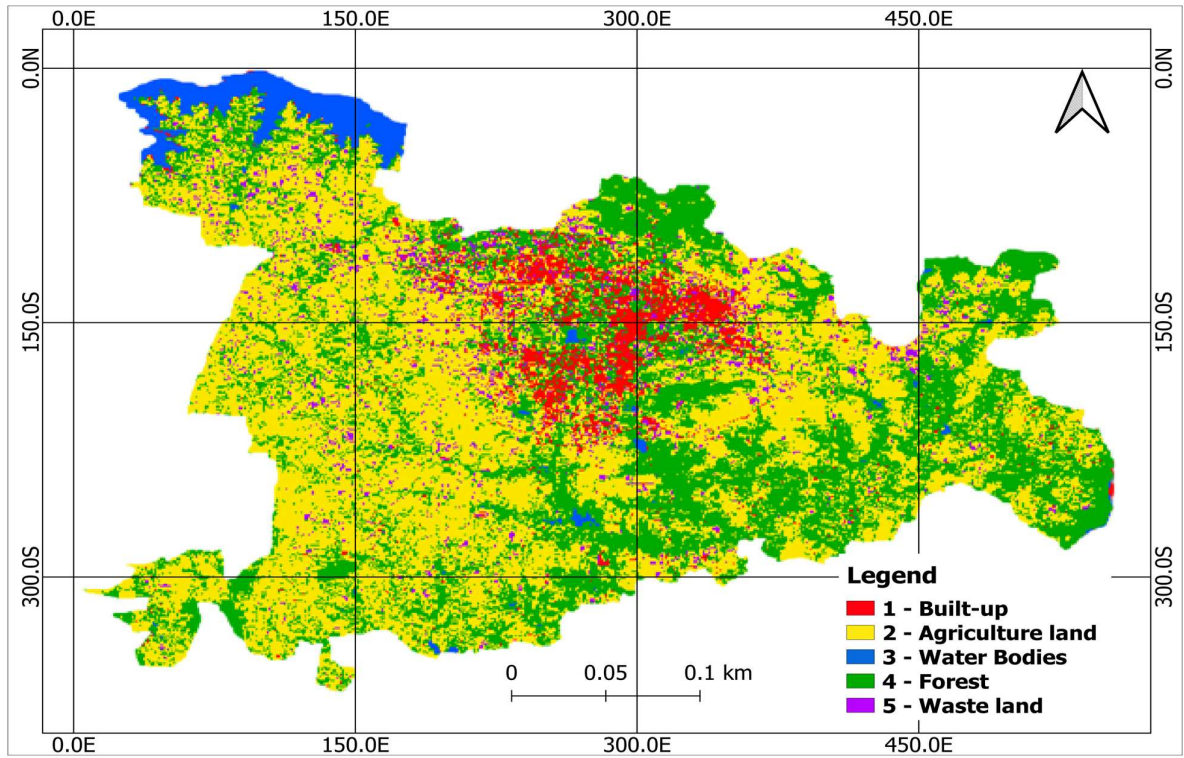


Fig. 7: Classified map of Mysuru taluk using CNN-FE.

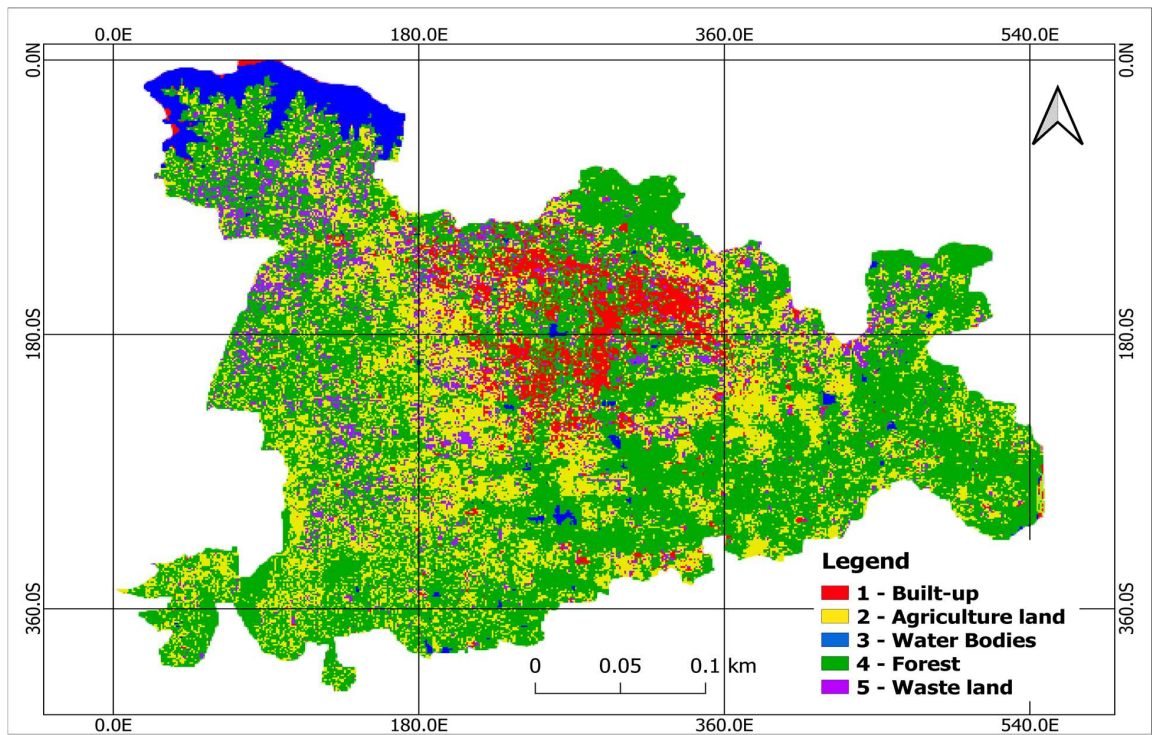


Fig. 8: Classified map of Mysuru taluk using transfer learning.

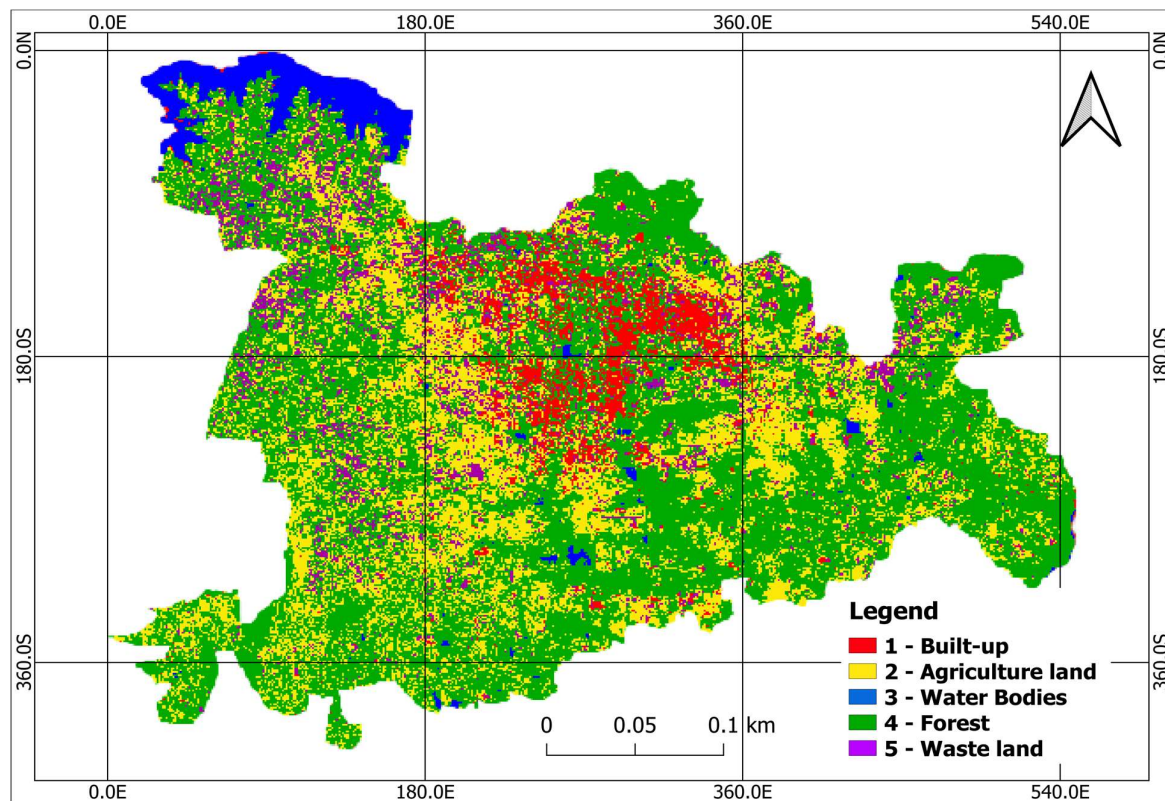


Fig. 9: Classified map of Mysuru taluk using Fine-tuning.

such as the kappa value, precision, recall, and F1 score were employed to assess performance across different classes. The results for the CNN-FE, transfer learning, and fine-tuning models are presented in Tables 3, 4, and 5, respectively. The F1 score, which provides an average performance measure for the models and individual classes, is calculated as the harmonic mean of accuracy and recall. A high F1 score indicates balanced precision and recall for that class, whereas an F1 score of zero signifies that the model fails to make any predictions when either accuracy or recall is zero.

According to the classification results, the transfer learning model achieved a 100% F1 score for the built-up class (Table 4), while the CNN-FE model scored 100% for the agriculture land class (Table 3), and the fine-tuning model also scored 100% for its respective class (Table 5). Accuracy and loss metrics further illustrate the suitability of the DL models, these are depicted in Figs. 4, 5, and 6 for the CNN-FE, transfer learning, and fine-tuning models, respectively. The figures show the training accuracy (blue curve) and validation accuracy (red curve) steadily increasing with the number of epochs. We minimized errors in the models' performance by utilizing cross-entropy loss.

Table 3: CNN-FE classification performances.

Classes of LULC	Precision	Recall	F1-Score
Built-up	0.95	0.95	0.90
Agriculture land	1.00	1.00	1.00
Water Bodies	0.73	0.95	0.84
Forest	0.86	0.95	0.90
Waste land	0.91	0.75	0.83

Table 4: Transfer learning classification performance.

Classes of LULC	Precision	Recall	F1-Score
Built-up	1.00	1.00	1.00
Agriculture land	1.00	0.95	0.96
Water Bodies	0.69	0.90	0.78
Forest	0.82	0.90	0.86
Waste land	0.95	0.90	0.92

Table 5: Fine-tuning classification performance.

Classes of LULC	Precision	Recall	F1-Score
Built-up	1.00	0.90	0.98
Agriculture land	1.00	1.00	1.00
Water Bodies	0.76	0.95	0.83
Forest	0.87	0.88	0.90
Waste land	0.94	1.00	0.95

Confusion Matrix

In this research work, we applied deep learning models for the classification of LCLU on satellite images. Several metrics have been used to evaluate DL models' performance. Initially, we employed a confusion matrix to assess class performances and overall accuracy of each DL model, along with recalls, F1-score, and precision. Similar to the F1-score, the confusion matrix measure shows improved class performance in the majority of classes. Figs. 10, 11, and 12 show the confusion matrix constructed for DL models of CNN-FE, transfer learning, and fine-tuning, respectively. It takes into account each true labeled class in a row and the predicted labeled class in columns. The diagonal intersection's probability score indicated which classes were correct. On the other hand, it is anticipated that the results in the remaining rows and columns will belong to incorrect classes.

Fig. 11 presents the confusion matrix analysis for the CNN-FE model, illustrating its performance across various classes. Each column indicates the expected class, while each row corresponds to the true class. Diagonal elements represent correctly classified instances, whereas off-diagonal elements denote misclassifications. Analyzing these values reveals the model's strengths and areas needing improvement in classifying different categories. High values along the diagonal reflect strong classification accuracy, while off-diagonal values indicate potential confusion points. These insights can inform further refinement of the CNN-FE model architecture or dataset preprocessing to enhance overall accuracy.

Fig. 12 provides the confusion matrix analysis for the transfer learning model, offering a detailed view of its classification performance. By leveraging pre-trained weights from a different task or domain, the transfer learning model adapts its knowledge to the target classification problem. Similar to the CNN-FE analysis, the matrix shows correct and incorrect classifications across classes, with discrepancies apparent in off-diagonal elements. These results demonstrate how transfer learning leverages prior knowledge to improve classification, while also highlighting areas where additional fine-tuning could boost performance.

Fig. 13 displays the confusion matrix analysis for the fine-tuning model, offering further insights into its classification capabilities. Fine-tuning involves training a pre-trained model on a new dataset with a small learning rate, enabling it to adapt to the specific task while preserving learned features. Examining the distribution of correct and incorrect classifications across classes helps assess the effectiveness of fine-tuning. This analysis highlights differences between predicted and actual labels, guiding adjustments to improve classification accuracy and model efficiency.

The results of deep learning models applied to LULC classification are shown in Table 6. The findings indicate that the proposed models successfully adapted to remote sensing tasks, with the CNN-FE, built from scratch, performing noticeably less well than transfer learning and fine-tuning models.

The experimental outcomes show a progressive increase in accuracy across the three models. The CNN-FE achieves

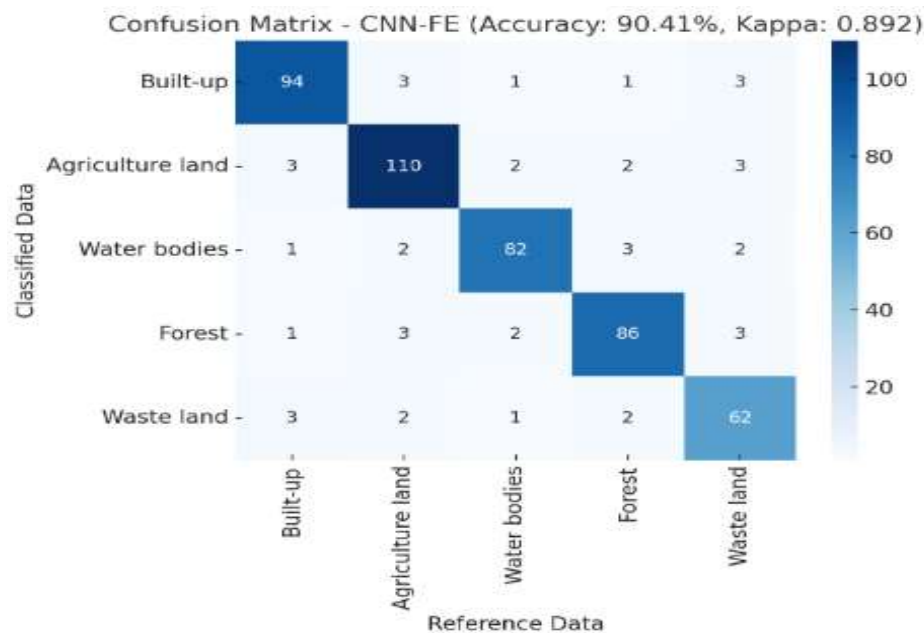


Fig. 10: Confusion matrix of CNN-FE.

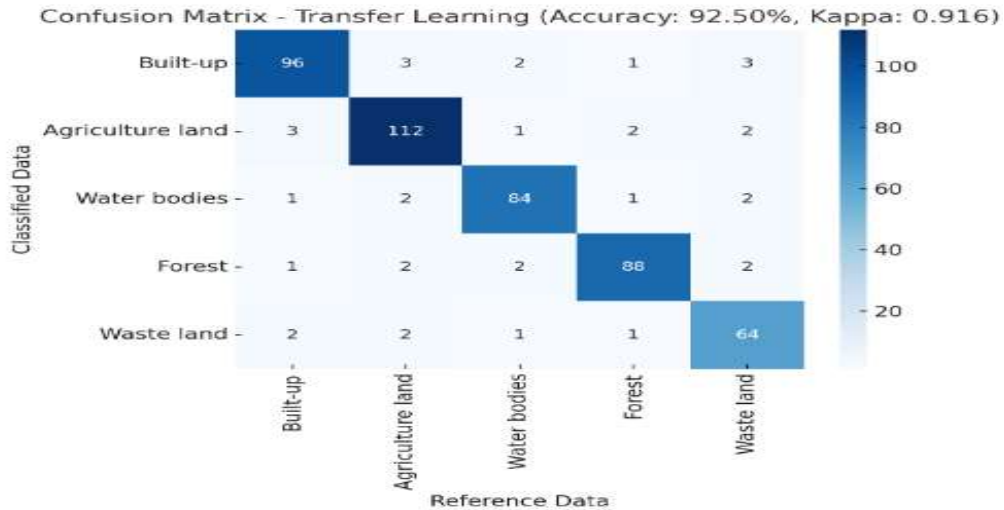


Fig. 11: Confusion matrix of transfer learning.

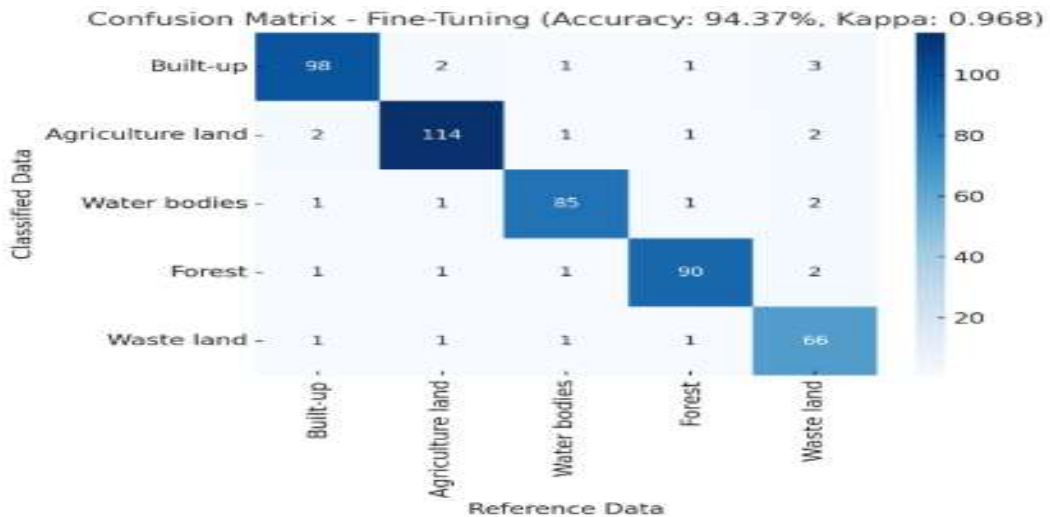


Fig. 12: Confusion matrix of fine-tuning.

Table 6: DL models' performance analysis using various performance matrices on satellite data.

DL Models	Performance Metrics					Training Time [s]	Testing Time [s]
	Precision [%]	Recall [%]	F1-Score [%]	Accuracy [%]	Kappa value		
CNN-FE	89.00	92.00	89.00	90.41	0.892	278.5	94.3
TRANSFER LEARNING	89.20	93.00	90.40	92.50	0.916	165.6	51.9
Fine-tuning	91.40	97.40	93.20	94.37	0.968	132.7	35.4

an accuracy of 90.41%, demonstrating effective feature extraction. Transfer learning improves this to 92.50%, while fine-tuning yields the highest accuracy of 94.37%. These results underscore the value of methodological refinement and model optimization, with fine-tuning particularly beneficial for adapting pre-trained models to specific tasks and achieving superior classification performance.

The performance of three deep learning models, CNN-FE, transfer learning, and fine-tuning, is detailed in Table 6, evaluating precision, recall, F1-score, accuracy, and kappa value. CNN-FE demonstrated strong results, with a precision of 89.00%, recall of 92.00%, F1-score of 89.00%, accuracy of 90.41%, and a kappa of 0.892. These metrics reflect CNN-FE's effective ability to classify accurately

within the dataset, balancing precision and recall. Transfer learning showed slight improvements across most metrics, achieving a precision of 89.20%, a recall of 93.00%, an F1-score of 90.40%, an accuracy of 92.50%, and a kappa of 0.916, indicating a performance boost through leveraging pre-existing knowledge. Finally, fine-tuning outperformed the other two models, with a precision of 91.40%, a recall of 97.40%, an F1-score of 93.20%, an accuracy of 94.37%, and a high kappa of 0.968. These results demonstrate the superior effectiveness of fine-tuning for LULC classification, yielding significant improvements across all metrics. The training and testing times for these models are also presented in Table 6. CNN-FE required 278.5 seconds for training and 94.3 seconds for testing. Transfer learning was more efficient, with training taking 165.6 seconds and testing 51.9 seconds. The fastest was fine-tuning, with a training time of 132.7 seconds and testing time of 35.4 seconds. These findings highlight the varying computational demands, confirming that fine-tuning is the most time-efficient approach.

Comparison of State-of-the-art Methods

The comparative analysis of the proposed CNN-based deep learning models with existing classifiers highlights the effectiveness of our approach when applied to the LISS-III dataset. Unlike previous studies that reported results on different datasets such as Sentinel-2, Landsat-8, or other high-resolution imagery, this research implemented and uniformly evaluated various researchers' models on the same LISS-III dataset. This approach ensures a fair and unbiased comparison by eliminating variations caused by differences in spatial resolution, sensor characteristics, and study regions.

As shown in Table 7, the three proposed models—CNN-FE, TL, and FT—consistently outperformed traditional classifiers. Of these, the fine-tuning approach achieved the highest accuracy of 94.37% with a Kappa coefficient of 0.968, significantly surpassing classifiers such as k-NN

(87.28%), Decision Trees (83.24%), SVM (86.71%), MLC (85.42%), and RF (88.93%). This underscores the superiority of deep learning techniques in capturing complex spatial-spectral features from medium-resolution imagery.

Compared to CNN architectures reported in earlier studies (Hosseiny et al. 2022, Yao et al. 2020, Bryan Sencaki et al. 2023), our fine-tuned CNN demonstrated notable improvements. Yao et al. (2020) achieved 92.65% accuracy, whereas our fine-tuned model reached 94.37% on the same dataset. Similarly, the transfer learning model attained 92.50% accuracy, confirming the adaptability of pretrained networks to LISS-III data. These comparisons indicate that the proposed models not only generalize effectively but also improve performance under identical experimental conditions.

It is also important to note that many prior studies reported promising accuracies based on higher-resolution datasets, making direct comparisons with medium-resolution LISS-III data less scientifically valid. In contrast, applying these models directly to our LISS-III dataset provides a methodologically sound and reliable basis for comparison. The results confirm that, with proper adaptation, LISS-III imagery can achieve classification accuracies comparable to or surpassing those obtained from higher-resolution datasets.

Furthermore, the higher Kappa values observed—particularly 0.968 for the fine-tuned CNN—highlight the robustness of our models, reducing the likelihood of chance agreement. This not only reflects higher overall accuracy but also indicates stronger class-specific agreement, which is crucial for land use and land cover (LULC) mapping.

In conclusion, the findings clearly demonstrate that our proposed CNN-based deep learning models, especially the fine-tuned variant, outperform both traditional classifiers and existing CNN implementations from other studies for LULC classification using LISS-III data. Conducting

Table 7: Proposed CNN-based DL model comparison with existing classifiers.

Classifier	Proposed DL models			Hosseiny et al. (2022)	García-Gutiérrez et al. (2010)	Zaabar et al. (2022)	Punia et al. (2011)	Yao et al. (2020),	Bryan Sencaki et al. (2023)	Zerrouki et al.(2019)	Dlamini et al. (2021)	Vivekananda et al. (2021)	Pande (2022)
	CNN-FE	TF	Fine-tuning	CNN	k-NN	CNN	DT	CNN	CNN	WRF	SVM	MLC	RF
Accuracy(%)	90.41	92.50	94.37	92.74	87.28	92.65	83.24	91.24	90.62	86.15	86.71	85.42	88.93
Kappa Value	0.892	0.916	0.968	0.901	0.845	0.912	0.824	0.904	0.894	0.874	0.846	0.832	0.861

controlled, dataset-consistent comparisons affirms that medium-resolution Indian remote sensing imagery can be effectively utilized for high-accuracy land use monitoring through advanced deep learning techniques.

CONCLUSIONS

This research paper introduces deep learning models designed to improve the accuracy of land use and land cover (LULC) classification. The CNN-FE model was built and trained from scratch, while transfer learning and fine-tuning models utilized pre-existing frameworks. The performance of these models was evaluated using metrics such as precision, recall, F1-score, accuracy, and the kappa coefficient. Results indicate that fine-tuning achieved the highest performance across all metrics, with precision at 91.40%, recall at 97.40%, F1-score at 93.20%, and accuracy at 94.37%. Transfer learning also showed strong results, with a precision of 89.20%, a recall of 93.00%, an F1-score of 90.40%, and an accuracy of 92.50%. Although CNN-FE lagged slightly behind, it still produced acceptable outcomes with precision at 89.00%, recall at 92.00%, F1-score at 89.00%, and accuracy at 90.41%. These findings have significant implications for applications such as urban planning, environmental monitoring, and natural resource management, where accurate LULC classification is crucial for making informed decisions and promoting sustainable development.

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