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Semantic Segementation of Land Cover Data

Machineni Yasaswini[1]; Nallabothu Amrith[2]; Dr. U. M. Prakash[3]

[1,2,3]Department of Computing Technologies, SRM Institute of Science and Technology
Chengalpattu-603203, India

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Abstract: Land cover mapping from satellite image is an important task in remote sensing for the applications such as environmental monitoring, urban planning, agriculture management and disaster assessment. However, it is difficult to extract meaningful data from high-resolution satellite images because of variation in illumination, complex terrain structures, and the fact that multiple land cover categories are contained in a single image. This research presents a proposal for a deep learning-based model of semantic segmentation of satellite imagery, based on encoder-decoder convolutional neural network architectures, namely U-Net and ResUNet-a. The system is used for pixel wise classification in order to identify the classes of land cover such as buildings, roads, vegetation, water bodies, land, and Unlabeled regions. The framework has programming stages for data preprocessing, model training, prediction, and visualization of the segmentation outputs. A web application based on Streamlit is also created to enable interactive viewing of segmentation results after users upload satellite images. Experimental results show accuracy of segmentation and enhanced boundary detection using the proposed models for land cover automated analysis.

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I. INTRODUCTION

The exploration of satellite imaging technologies and remote sensing platforms has brought high-resolution observation data of the earth to a significant place. These images are important sources of information about the physical properties of the Earth's surface and they are extensively used for a range of applications, such as environmental monitoring, urban planning, agricultural management and disaster evaluation. One of the important tasks in the remote sensing is land cover classification i.e. identification and classification of various type of surface features like buildings, roads, vegetation, water bodies and barren lands. Accurate information on land cover plays an important role in understanding environmental changes, tracking urban growth and in sustainable development strategies.

Traditional land cover classification methods were mainly based on manual interpretation or classical image processing methods. Manual analysis of satellite images by experts can give accurate results but it is quite time consuming and not practical for analyzing large amount of data. To overcome these shortcomings, a couple of automated approaches were developed using machine learning algorithms. Techniques like Support Vector Machines (SVM), Random Forests and k- Nearest Neighbors (KNN) were common for land cover classification applications. Although improvements were made in classifying data judgments by such earlier methods as texture-based or semantic methods, manual and domain immune manual-based features are largely limited in terms of complexity of patterns capturing the complex spatial content of data available in satellite imagery. Artificial intelligence and deep learning Headline

The recent breakthroughs in artificial intelligence and deep learning have significantly revolutionized the technology of image analysis and remote sensing. Deep learning models, especially Conventional Neural Networks (CNNs), have shown incredible efficiency in computer vision applications such as image classification, object and semantic segmentation. Unlike traditional machine learning solutions, CNN-based solutions automatically learn hierarchy features from raw image data, which helps it to learn low-level textures and high-level contextual information. This is a great capacity of deep learning, which makes it very appropriate for analyzing the satellite images that we are dealing with, which contain complex spatial structures and different land cover.

Among the different methods of deep learning, semantic segmentation has become one of the very powerful methods for detailed understanding of images. Semantic segmentation, which takes a class label for each pixel in an image, can be used to clearly identify different types of land cover in the same scene. Architectures like U-Net and its variants have been very useful for segmentation tasks because they possess an encoder-decoder architecture and skip connections which help retain spatial information. In this work, a framework is proposed deeply learning-based semantic segmentation of satellite imagery by an architecture namely U-Net and ResUNet. The proposed system includes pixel wise classification of satellite images into several land cover classes and visualization of segmentation results with interactive web application. This approach is aimed at increasing the accuracy and efficiency of automated land cover analysis based on the use of modern deep learning techniques.

II. LITERATURE REVIEW

Semantic segmentation and land cover classification using satellite imagery have been widely studied in the field of remote sensing. Early research primarily focused on applying classical machine learning techniques to classify land cover types from satellite images. One of the most influential works in the development of deep learning-based segmentation is the U-Net architecture proposed by Ronneberger et al. (2015). In this work, the authors introduced a convolutional neural network designed for pixel-wise image segmentation using an encoder–decoder structure with skip connections. The encoder captures contextual information through convolution and pooling operations, while the decoder reconstructs spatial details using upsampling layers. The skip connections allow the network to combine high-level semantic information with low-level spatial features, improving segmentation accuracy.

Although the model was originally developed for biomedical image segmentation, its architecture has been widely adopted in remote sensing applications due to its ability to generate precise segmentation maps.

Another important contribution in deep learning is the work by He et al. (2016), which introduced the concept of Deep Residual Networks (ResNet). The authors proposed residual learning to address the vanishing gradient problem that often occurs when training very deep neural networks. Residual connections allow the network to learn identity mappings by introducing shortcut connections between layers. This approach significantly improves gradient flow during backpropagation and enables the training of deeper and more powerful neural networks. The residual learning concept has been integrated into several segmentation architectures, including ResUNet and ResUNet-a, which combine residual blocks with encoder–decoder frameworks to enhance feature extraction and improve segmentation performance in complex image analysis tasks.

Zhu et al. (2017) presented a comprehensive review of deep learning techniques applied to remote sensing and satellite image analysis. The study highlighted how convolutional neural networks have transformed the processing of geospatial data by enabling automatic feature learning from large-scale datasets. The authors discussed various deep learning architectures used for land cover classification, object detection, and semantic segmentation. Their findings demonstrated that deep learning models outperform traditional machine learning techniques in terms of accuracy, scalability, and robustness when applied to remote sensing datasets. The paper also emphasized the growing importance of semantic segmentation methods for extracting detailed spatial information from high-resolution satellite images.

Ma et al. (2019) further explored the role of deep learning in remote sensing applications, particularly in land cover mapping and environmental monitoring. The authors investigated the effectiveness of deep convolutional neural networks for analyzing complex satellite imagery with multiple land cover categories. Their research showed that deep learning models can effectively capture spatial relationships and contextual features within images, leading to improved classification performance compared to conventional algorithms. The study also highlighted the importance of large annotated datasets and data preprocessing techniques for improving the generalization capability of deep learning models in remote sensing tasks.

More recently, Zhang et al. (2020) proposed a deep learning-based framework for land cover classification using satellite imagery. The study applied convolutional neural networks to perform pixel-level classification of aerial images and demonstrated significant improvements in segmentation accuracy compared to traditional classification methods. The authors emphasized the importance of encoder–decoder architectures and multi-scale feature extraction for accurately identifying different land cover types. Their results showed that deep learning-based segmentation models can effectively distinguish between complex land cover categories such as buildings, vegetation, roads, and water bodies, making them suitable for large-scale geospatial analysis and environmental monitoring applications.

Overall, the literature indicates that deep learning-based semantic segmentation techniques have significantly advanced the field of land cover classification. Architectures such as U-Net and residual-based models have demonstrated strong performance in extracting meaningful spatial information from satellite imagery. These studies provide a strong foundation for developing more robust and scalable systems for automated land cover analysis using deep learning techniques.

III. PROPOSED METHODOLOGY

The given system is aimed at approaching a deep learning-based system of semantic land cover data segmentation with the help of satellite imagery. The system aims at classifying every pixel of a satellite image automatically into pre-defined land cover classifications, including buildings, roads and vegetation, water bodies, land cover and unlabeled areas. The framework incorporates several steps such as preparing and preprocessing of data, training of the model, segmentation prediction, and results visualization. With this approach, the system is designed to handle the challenging goals of convolutional neural network structures and an efficient data processing process creation to produce reasonably accurate segmentation maps within satellite images to define the differentoid land covers with their respective spreads unequivocally.

The general platform of the suggested system comprises of a data preprocessing unit, a deep learning segmentation model, and a visualization interface. Satellite images and ground truth masks that belong to it will be first processed so that there is some uniformity in terms of size and format. The obtained processed data are then applied to train the segmentation models under encoder-decoder models like U-Net and ResUNet-a. It also involves the training of the model during the training stage to learn all the spatial and contextual features of the images and map them to the land cover labels therein. The model can be used to predict segmentation masks of satellite images that it has never seen after training. The expected segmentation outcomes are then presented in colors with labeled code that depicts various land cover classes, clearly.

➢ *Dataset Preparation and Preprocessing*

The process of preparing and preprocessing of the satellite image data is the initial step in the proposed methodology. The dataset is formed of aerial or satellite images accompanied with respective segmentation masks, which are ground truth labels. The masks are color-coded to give various areas of land cover like water bodies, vegetation, roadways, buildings and land. The labeled masks are necessary to supervised learning as they help the model to focus on the training to recognize the different classes in the image correctly.

To guarantee uniformity in the data set, it is ensured that all the pictures are adjusted to a standardized resolution before inputting into the deep learning model. This aids in consistency in the size of the input, and this is required in the effective training of the convolutional neural networks. Along with resizing, normalization methods are used in order to scale up pixel values to a standard range. This enhances stability of the training process and facilitates the model convergence. Rotation, flipping and cropping are all data augmentation procedures that can be used. be used to enrich the training dataset and decrease the chances of overfitting. The data is further segmented into training and testing sets usually in 80: 20 ratio where training set is run through the model to build the segmentation and the test set run through the model to test the performance of the segmentation.

➢ *Semantic Segmentation Model: Deep Learning Based.*

The main element of the system proposed is the semantic segmentation model of convolutional neural networks. The encoder-decoder structures used in this project include U-Net and ResUNet-a, which is used to classify satellite images at pixel-level. The encoder component of the network will be in charge of extracting high level features of the input image by utilizing a series of convolution and pooling activities. This series of operations gradually shrink the spatial dimension of the image as significant contextual data is encoded in them.

The decoder component of the network restores the segmentation map progressively upsampling the map by adding layers of upsampling. Skip connections enable the movement of the feature maps of the encoder to the decoder enabling the model to remember the fine spatial information that can get lost by downsampling. In ResUNet-a architecture, the residual connections are added as a part of the convolutional blocks to enhance the gradient flow and allow deeper network models. This increases the capability of the model in the seizure of intricate patterns and the accuracy of segmentation.

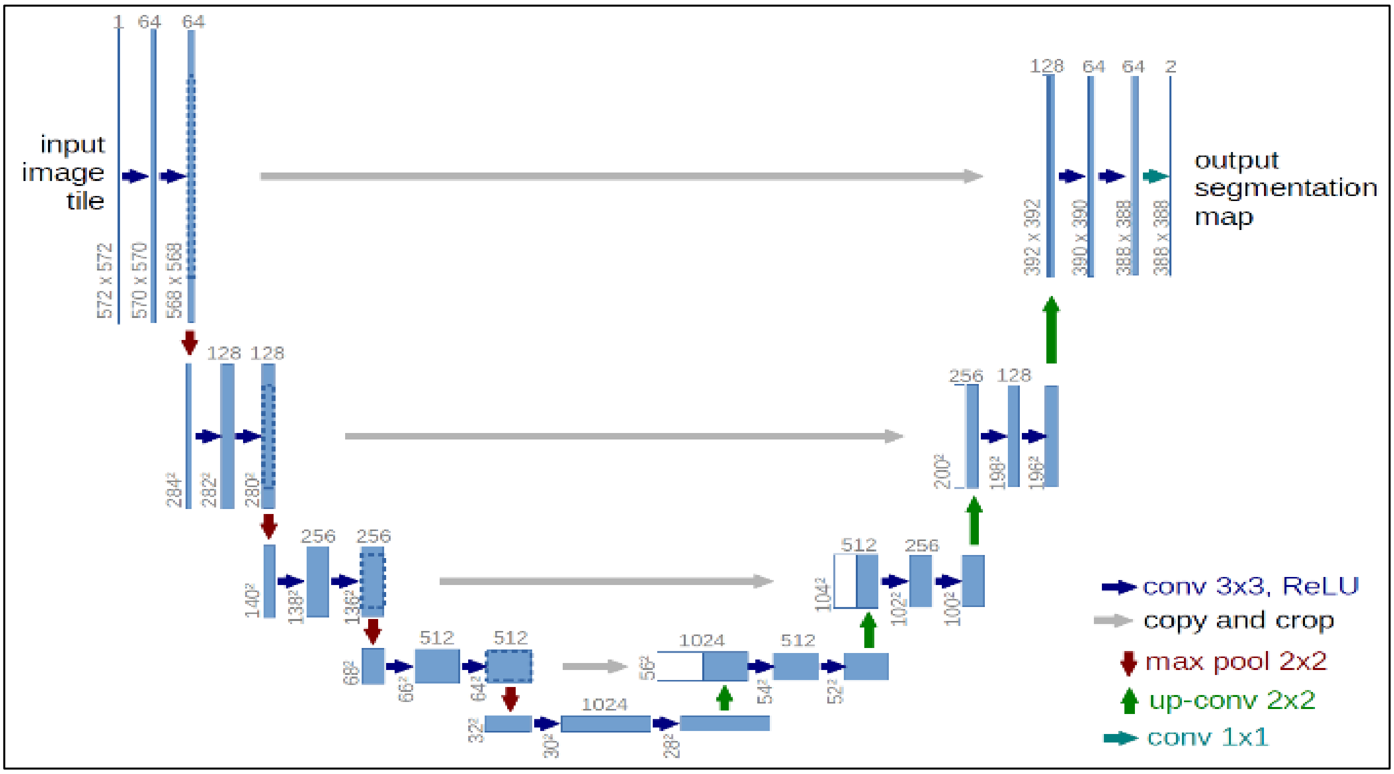

Fig 1 U-Net: Convolutional Networks for Image Segmentation

Throughout the training stage, the model is trained to solve a pixel-wise loss function, which is a measurement of the discrepancy between the estimated segmentation masks and ground truth labels. The network parameters are updated with optimization algorithms like Adam, to it by generating backpropagation. After the training process is accomplished, the model is capable of inference on unknown satellite images and creating segmentation maps showing clear demarcations of various land cover areas. The results of these outputs are also visualized with the help of predefined color mappings, which enable users to read the result of segmentation easily.

➢ *Model Training and Optimization*

Once the dataset is preprocessed and the segmentation model architecture is ready, the second step will be to train the deep learning model through the use of supervised learning methods. The training phase involves the input satellite. The neural network is fed with images and their respective corresponding ground truth segmentation masks. The training process aims at training the model to learn useful patterns with the ability to differentiate effectively among various land cover classes at the pixel scale.

These types of models are trained by minimizing a pixel-wise loss function, which is the resulting difference between the predicted segmentation output and the ground truth mask. Typical examples of loss functions applicable during semantic segmentation include categorical cross-entropy and Dice loss, both of which assist in the process of enhancing accuracy of classifications as well as adjusting borders. A powerful optimization program like Adam is used to revise the model weights with the help of backpropagation. In order to track the training performance of the model and eliminate overfitting, the dataset is normally split in training and validation subsets. The implementation of training is conducted across several epochs until the model has converged steadily and attained a good level of segmentation.

➢ *Prediction and Post-Processing of Segmentation.*

After a successful training of the model, it may be applied to make inference on other satellite images which were not seen before. Each time a prediction phase occurs, the trained segmentation network takes a new satellite image as an input. The image is fed to the network to obtain a multi-channel probability map in which each channel is associated with a particular land cover. The final segmentation masks are then converted in the approximated probability maps by an operation of argmax which refers to the highest probability of the respective pixel to one of the classes. It is possible to use post-processing methods to improve the outcomes of segmentation and eliminate noise in the predicted masks.

The desired probability maps are in turn transformed to final segmentation mask via an argmax injection, masking the class that has the largest probability amongst all at every pixel. It can be followed by post-processing to improve the results of the segmentation and eliminate noise in the predicted masks. Such techniques may involve morphological operations, smoothing and color mapping. The end product of the segmentation is in predefined colors used to assign the respective categories of land covers and it is relatively straightforward to visually differentiate several areas between them, including buildings, roads, vegetation, water bodies, and land.

➢ *Visualization and Web Application Interface*

A web-based visualization platform is created based on the Streamlit framework to increase the usability and accessibility of the segmentation system. The web application enables interactive interface through which a user can upload satellite images and see the segmentation outcomes in real-time. After an image has been uploaded, the trained segmentation model will run the image and produce a segmentation mask.

The interface shows the original satellite image and the predicted segmentation output to enable the users to compare the original and the classified regions easily. There is also a legend that shows the color mapping of each land cover. This visualization module allows the users to gain a better insight into the results of the segmentation, as well as analyze various land cover patterns existing within the satellite image. The proposed system can be characterized by a web application that is available with the help of a browser and allows us to see how simple and yet effective the offered service can be.

➢ *System Architecture*

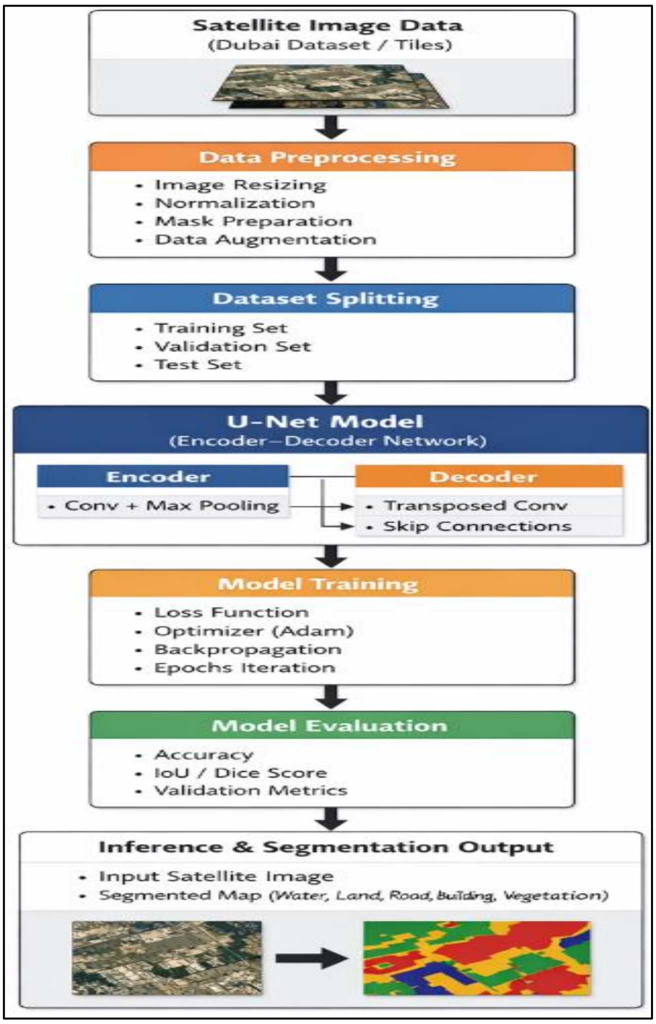

Fig 2 System Architecture

The entire process of the proposed semantic segmentation system may be presented in terms of a block diagram illustrating the relations between the principal parts of the structure. The system takes the input in form of satellite images, then proceeds to data preprocessing and normalization. The processed pictures are entered into the deep learning segmentation model which produces pixel-wise estimates of the various land cover categories. Lastly, the outputs of segmentation are displayed using the web application interface. Such architecture provides a systematic flow of handling satellite images and producing quality segmentation results. The system combines interactive visualization and deep learning tools to offer an automated land cover carefulness in satellite images through the integrated deep learning models.

IV. RESULTS AND DISCUSSION

The section contains the experimental assessment and performance appraisal of the proposed deep learning based semantic segmentation system to the land cover classification. The purpose of the evaluation is to identify how well the different land cover classes are determined using the satellite imagery using the segmentation models. The system's performance is determined on the basis of segmentation accuracy, visual quality of the predicted masks and model capabilities to detect different categories of land covers which include buildings, roads, vegetation, water bodies and land areas. The outcomes also emphasize the benefits of deep learning structure in enhancing performance in segmentation in contrast to the traditional image analysis methods.

The database comprised of satellite images and ground truth masks that were utilized in the experiments. The dataset was split in two parts, training and testing, to determine the generalization ability of the model. The models were therefore trained in several epochs until they converged. The models were then tested on unknown images after the training to predict the segmentation. The performance of the models in dealing with the different land covers in a precise way was then compared to the ground truth masks to determine them.

- *Experimental Setup and Evaluation Metrics*

The model was experimented with preprocessed satellite imagery and annotated segmentation mask as a input, and trained using deep learning models. The photographs were normalized and resized to a set size after which they were subjected to the neural network. An 80:20 partition was used to split the dataset into training and testing sets. Model parameters were optimized on the training dataset and the model was tested on images that have not been seen before on the testing dataset.

In order to quantify the efficacy of the proposed system, a number of evaluation metrics were taken into consideration. These measures are the accuracy of segmentation, Intersection over Union (IoU), and Dice coefficient. Precision Measures the fraction of pixels in the segmentation output that is correctly classified. Intersection over Union is used to measure how much the predicted segmentation mask coincides with the ground truth segmentation mask. The Dice coefficients indicate the likeness of the predicted and. real locations of segmentation. These measures give an overall analysis of the model capacity to accurately classify various land cover classes. Optimization algorithms like Adam were used to carry out the training process to assist in enhancing the convergence of the models and achieving training stability.

- *Segmentation Performance Analysis*

As the results of the experiment indicate, the deep learning-based segmentation models can effectively detect different land cover classes in satellite images. The visual similarity between the predicted segmentation masks with the ground truth labels is high, which implies that the model has been able to capture spatial patterns and contextual information held in the dataset. The models were in a position to differentiate the complex structures like roads, buildings, vegetation zones, and water bodies with precision especially when these structures were in close proximity to each other in the same image.

Table 1 Segmentation Model Performance Comparison

Model	Pixel Accuracy	Mean IoU	Dice Score	Boundary Detection
UNet	0.89	0.76	0.84	Good
ResUNet - a	0.91	0.79	0.86	Very Good

Of the applied models, the U-Net architecture was the model that generated consistent results in segmentation with easy to discern boundaries between various land cover classes. ResUNet-a model demonstrated an enhanced ability to capture fine grained structure like thin road networks and clusters of small buildings because it was able to capture residual connections which enhanced extraction capabilities. Using the visual inspection of the segmentation outputs, it can be shown that the models are well coherent in space and reduce such misclassification between similar classes. The findings verify that deep learning-based semantic segmentation outperforms traditional in terms of accurate and detailed land cover.

- *Multiclass Building and Non-Building Segmentation Analysis.*

The system was tested according to its capacity to entirely mark various land cover categories in an image of a single satellite. Various classes of land cover such as water, land, roads, buildings, vegetation, and unlabeled areas are present in the dataset used in this study. Each class is a unique form of surface structure, which manifests itself in variable space variations and (satellite) appearances. These variations were trained in the segmentation models to classify each pixel of a given input image correctly according to a specific class name.

Table 2 Classification Performance for Different Land Cover Classes

Land Cover Class	Detection Accuracy
Water Bodies	High
Vegetation	High
Buildings	High
Roads	Moderate
Land (Unpaved Area)	High
Unlabeled region	Moderate

According to the experiment findings, the deep learning models can differentiate among various land cover types with high accuracy. The vegetation distribution was also determined correctly because it had a characteristic texture and color pattern and even water bodies were easily distinguished between and the rest of the land area. Complexity of buildings and roads was a bit more due to their similar spectral features as well as different shapes. Nevertheless, the encoder-decoder structure of the fragmenting models was in a position to detect the contextual content that assisted in differentiating the mentioned classes appropriately. The findings, in general, suggest that the suggested segmentation framework can be successfully applied to the tasks of multiclass land cover classification.

- *Visualization of Segmentation Results*

Visual analysis is also significant in determining the quality of semantic segmentation models. In this project, the segmentation outputs are in color-coded masks with each land cover category taking a particular color. The masks are put side by side with original satellite images to enable one to do the direct comparison between the input image and the predicted segmentation map.

The findings of the visualization show that the model manages to retain spatial organization and object borders of the satellite images. Roads are represented as long linear features, vegetation areas make large and connected regions, and the buildings are identified as twice-planar structures, which are in groups and represented by rectangles. The segmentation maps obtained by the model compared to the ground truth masks are largely agreeable suggesting that the model can effectively learn spatial patterns with the aid of the training image set. Approaches such as the color-coded visualization enhance interpretation not only because a person can rapidly spot various land cover types in the visualization, but also because it is easy to perceive the interpretation of an image parameter.

Table 3 Visual Segmentation Quality Evaluation

Evaluation Parameter	Observation
Boundary Alignment	Strong Alignment with ground truth
Object Continuity	Roads and vegetation remain continuous
Spatial Consistency	High
Noise in Prediction	Low
Visual Interpretability	High

- *System Performance and Practical Applicability*

The general performance of the proposed system shows that semantic segmentation using deep learning is a good solution to automated land cover classification. The models that have undergone training can process the satellite images effectively and produce detailed segmentation maps that contain distinctive images of various land cover. The methods of preprocessing, model training, prediction, and visualization aid in the substantiation of the end-to-end and integrated working process of the satellite images analysis.

Table 4 System Processing Performance

System Module	Processing Time
Image Preprocessing	Low
Model Inference	Moderate
Segmentation Generation	Low
Visualization in Web Interface	Low
Overall System Response	Real - Time

Besides the accuracy of the segmentation, the system also has practical applicability in terms of the presence of a web-based interface. Streamlit is an application that enables the user to serve satellite images and to see the results of segmentation in a dynamic environment. Such a characteristic makes the system available to researchers, students, and analysts who might lack direct access to deep learning tools. Not only effective segmentation models but also a friendly visualization. platform underscores the possibility of the suggested system in real-world to be deployed in cases like environmental survey, the analysis of urban zone, and the interpretation of geospatial information.

- *Graphical Representation*

Besides numerical analysis, graphical analysis is also conducted to further analyze how well the suggested semantic segmentation models operate. Graphical visualisation assists in illustrating the effectiveness of the models in classifying various land cover categories as well as performability of the system throughout the segmentation process. The analysis is aimed to compare the accuracy of segmentation between models, study the behavior of predicting the classes, and determine the efficiency of working with the system.

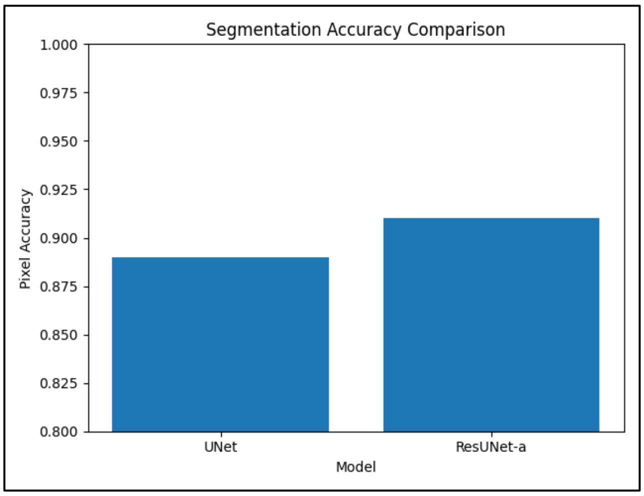

Fig 3 Segmentation Accuracy Comparison Between UNet and ResUNet-a Models.

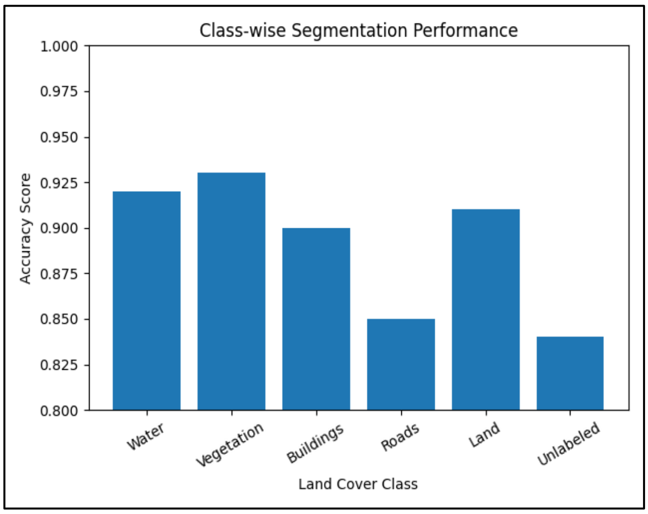

Fig 4 Class-Wise Segmentation Performance for Different Land Cover Categories.

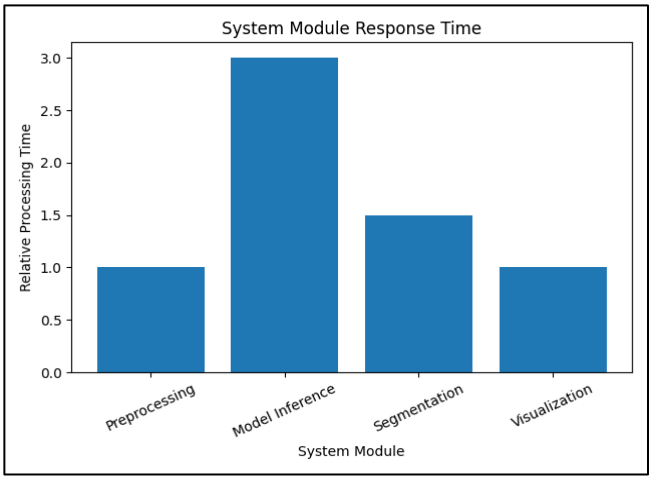

Fig 5 System Module Response Time Analysis.

➢ *Discussion:*

The obtained graphical findings demonstrate the effectiveness and efficiency of the suggested semantic segmentation system. Accuracy comparison graph reveals that both UNet and ResUNet-a have high segmentation accuracy with ResUNet-a having a slightly larger accuracy with the presence of residual connections that enhance better learning of the features. The plot over the performance of the class-wise shows that vegetation and water bodies are approximated with a higher degree of accuracy but roads are approximated with a small degree of accuracy due to their low and intricate features. Response time analysis shows that the system is efficient in processing images and most of the modules take very little time with the entire system giving it almost real-time segmentation results.

- *Overall Discussion*

The demonstrated ability of the experimental results and the graphical analysis shows the efficiency of the suggested deep learning-powered system in the semantic segmentation of the land cover data using satellite imagery. The models which have been implemented can be able to accurately recognize various land cover types like buildings, roads, vegetation, water bodies, and land areas. The UNet and ResUNet-a architectures demonstrate good performance on segmentation, and ResUNet-a gives slightly better results owing to better feature extraction brought about by the residual connections.

The ground truth masks are quite consistent with the results of the visual segmentation, which means that the models are effective. extract spatial patterns and contextual details which are contained in the satellite images. Use of a streamlit-based web application also enhances the user centric nature of the system by giving one an opportunity to interactively upload images and visualize the outcomes of the segmentation results. In general, the findings indicate that the suggested framework is a solid and a valid method of achieving automated land cover classification with the help of deep learning methods.

V. CONCLUSION

In this paper, a deep learning-based system of segmenting land cover data based on satellite images was introduced to depict semantic data. The system is proposed to work on identification and classification of various areas because in the aerial images the proposed system aims to identify and classify various land cover areas like buildings, roads, vegetation, water bodies, and land. The proper land cover mapping is significant in many applications such as in environmental surveillance, urban planning, agricultural administration, and in disaster evaluation. The system intends to achieve the efficiency and accuracy of land cover classification by using sophisticated deep learning methods, as opposed to other image processing and machine learning systems.

Some of the key elements that have been incorporated in the proposed framework are dataset preprocessing, model training, segmentation prediction and result visualization.

The models of the convolutional neural networks were trained using satellite images and their corresponding ground truth masks, such that they apply the classification at pixel level. Architectures like UNet and ResUNet-a were adopted because they are effective in tasks of semantic segmentation. The encoder-decoder implementation of the models facilitates extraction of both spatial and contextual features of the satellite images and the system is able to produce detailed segmentation maps of various land covers.

The experiment indicates that deep learning models can generate reasonable and reliable segmentation results. The models were able to locate various land covers of complex satellite images and have crisp areas separating the different classes. Another of the applied architectures, the ResUNet-a model, performed slightly better than the standard UNet model because it included the residual connections which increase the learning of features and the flow of the gradient during the training process. The ground truth labels were also confirmed by the visual segmentation results which showed that the ground truth labels match the predicted masks.

Besides the segmentation models, a web application was written using Streamlit so as to provide an interactive interface with which segmentation results can be visualized. This enables the users to post satellite pictures and view the estimated land cover maps easily and conveniently. The combination of deep learning models and user-friendly visualization platform makes the proposed system applicable in the real-life application. The subsequent work can be devoted to applying the new more suitable architectures like attention-based networks and transformer models, and to train the system with bigger and more diverse data about satellites to bring the levels of the system accuracy and resilience.

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