LAND ZONING USING SATELLITE IMAGERY AND MACHINE LEARNING

A PROJECT REPORT

Submitted by

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ABSTRACT

With rapid urbanization and growing pressures on land resources, effective land zoning has become essential for sustainable development. Land zoning involves categorizing land based on its suitability for different uses—residential, commercial, agricultural, or natural conservation. The structured approach aids in controlling urban sprawl, managing agricultural land, and protecting natural habitats, thereby promoting a balanced growth framework. Traditional land zoning methods often lack the adaptability and efficiency needed to handle high-resolution, diverse datasets, which limits their effectiveness in rapidly evolving landscapes. In the project, we utilize satellite imagery as a primary data source for land classification, leveraging its vast spatial coverage and real-time data capabilities. Using machine learning, specifically neural network architectures, the model processes patch-based satellite image data to identify land categories like residential zones, vegetation areas, and water bodies. Patch-based analysis helps in capturing granular details in land variation without relying solely on vegetation indices. The data-driven approach is particularly effective for distinguishing subtle land features, making it suitable for dynamic and complex land use scenarios. The neural network model is trained on a diverse set of labeled satellite images, allowing it to learn and generalize across different land types. By automating the classification process, the model significantly reduces the time and resources needed for land-use analysis. Hence it enables planners and policymakers to make faster, evidence-based zoning decisions, optimizing land utilization while addressing environmental concerns. The methodology not only advances the technical aspects of land zoning but also aligns with sustainable urban and rural development goals, offering a scalable and adaptable solution for modern land management needs.

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LIST OF ABBREVIATIONS

Adam - Adaptive Moment Estimation

CNN - Convolutional Neural Network

GIS - Geographic Information System

ML - Machine Learning

NN - Neural Networks

ReLU - Rectified Linear Unit

SDG - Stochastic Gradient Descent

SVM - Support Vector Machine

tf – TensorFlow

CHAPTER 1

INTRODUCTION

1.1 General

Data Land zoning and land classification are fundamental in urban planning and environmental management, focusing on how different land areas are designated for specific uses. Land zoning involves dividing a region into zones with regulated usage, such as residential, commercial, agricultural, or industrial, to ensure orderly development. This helps manage resources, reduce conflicts between land uses, and promote sustainability. Land classification categorizes the land based on characteristics like vegetation, water bodies, or barren areas. This classification is essential for understanding the land's suitability for various purposes, such as agriculture, conservation, or infrastructure development.

Satellite imagery plays a key role in these processes by providing high-resolution images of the Earth's surface over time, which enables accurate land assessments. Machine learning enhances this by processing and analysing vast amounts of satellite data, identifying patterns, and classifying land types with high accuracy. By training algorithms on labelled images, machine learning models can detect features like water, vegetation, or urban areas, supporting data-driven decision-making in land use planning and environmental protection.

Advancements in remote sensing and geospatial technologies have transformed how land zoning and classification are performed. Traditional methods of land classification, which were manual and often labour-intensive, are now enhanced by machine learning, which offers more efficient and accurate solutions. Satellite imagery provides large-scale data, capturing changes in land use over time, which is invaluable for environmental monitoring, urban expansion analysis, and disaster management. This integration allows for real-time or near-real-time insights, fostering proactive decision-making in land management.

In recent years, land zoning and classification have increasingly leveraged machine learning for predicting land use patterns, which is crucial in addressing urban sprawl and environmental challenges. By using high-resolution satellite data, machine learning models can monitor and predict changes in land use, offering insights into urban expansion, agricultural development, and natural resource management. This predictive capacity helps decision-makers plan ahead, fostering balanced growth and minimizing negative environmental impacts.

One significant benefit of machine learning in land classification is its scalability in processing vast datasets. Models trained on diverse geographic data can classify different land types, adapting to regional distinctions such as soil types, vegetation density, and water distribution. This adaptability makes machine learning an effective tool for land use planning across varied environments, from urban centres to remote agricultural regions, helping to preserve ecosystems while supporting development.

Another key advancement in this domain is the integration of multi-temporal satellite imagery, enabling the study of seasonal and long-term changes in land use. By analysing temporal patterns, machine learning models can identify trends such as desertification, deforestation, or urban growth. This temporal analysis is essential for developing sustainable land use policies, as it provides a data-driven approach to understanding environmental shifts and responding proactively to issues like climate change and resource depletion.

1.2 Motivation

Effective land management is becoming crucial amid urban expansion, climate change, and the rising demand for resources. As cities grow and natural and agricultural areas face increased development, it's essential to understand land use and assess areas for their suitability across diverse needs. Land zoning, which organizes land based on appropriate usage, is a vital strategy for balancing urban growth with environmental preservation. However, traditional zoning practices often rely on manual data collection and subjective evaluations, limiting their responsiveness to rapidly changing landscapes and diverse land-use demands.

Advancements in satellite imagery and machine learning offer transformative potential for land zoning. Satellite data provide comprehensive and up-to-date information across vast geographic areas, capturing details on terrain, vegetation, water bodies, and urban structures. When paired with machine learning, this data becomes actionable, as algorithms can rapidly analyse large datasets, identify patterns, and classify land based on predefined categories. Using automated, data-driven techniques enhances the objectivity and precision of zoning processes, helping planners make more informed, evidence-based decisions.

Implementing machine learning for land zoning also addresses global concerns around sustainable development. Automated classification based on satellite imagery aids in identifying land-use patterns, enabling better management of resources, protection of natural areas, and optimization of land for agricultural or industrial use. By leveraging this approach, stakeholders can more effectively respond to urban challenges and environmental threats, fostering a proactive approach to land use and ensuring that development aligns with long-term sustainability goals.

The integration of machine learning and satellite imagery in land zoning is transformative, offering a responsive approach to urban planning amid global challenges such as urbanization, climate change, and the need for sustainable resource use. Traditional zoning practices are increasingly supplemented with real-time data, allowing planners to detect shifts in land patterns and adjust zoning decisions dynamically. As models become more sophisticated, they can account for factors like ecosystem resilience and land suitability, driving sustainable development through data-informed decisions.

Moreover, automated classification supports rapid environmental assessments, essential for managing resources like water bodies, forested areas, and agricultural zones. By leveraging multi-spectral and high-resolution imagery, machine learning models provide valuable insights into land health, enabling strategies to protect ecosystems, mitigate deforestation, and optimize land for food production. These automated insights empower planners to anticipate environmental changes, balance development needs, and uphold long-term environmental resilience.

The approach also enables more equitable urban planning, as machine learning models can identify underserved areas and forecast land needs based on population growth trends. With high-accuracy classification, zoning decisions can align with demographic shifts, economic development goals, and social equity standards. This predictive capacity not only aids in resource conservation but also ensures that urban expansion supports diverse community needs, driving inclusive and sustainable growth.

1.3 Sustainable Development Goal of the Project

The project is intricately linked to the United Nations Sustainable Development Goal 15, which aims to safeguard, restore, and promote the sustainable use of terrestrial ecosystems. By employing advanced machine learning techniques in conjunction with satellite imagery for land zoning, the initiative provides critical insights into land use patterns and dynamics. This knowledge is essential for creating effective land management strategies that not only accommodate urban development but also prioritize the conservation of natural habitats and biodiversity.

The project addresses the growing challenge of land degradation by facilitating data-driven decisions that balance the needs of human populations with environmental sustainability. Moreover, the project encourages sustainable land utilization by offering a systematic approach to land classification, which helps identify areas suitable for various purposes, such as agriculture, urban development, or conservation. By accurately assessing land suitability, the initiative mitigates the risk of environmental degradation and promotes practices that benefit both communities and ecosystems.

CHAPTER 2

LITERATURE SURVEY

2.1 Background on Land Zoning

Land-use change and degradation on the Mongolian Plateau from 1975 to 2015 have been analyzed by Batunacun and colleagues [1], highlighting significant environmental impacts in the Xilingol region. Their findings underscore the dynamic interactions between human activities and land degradation, offering valuable insights into sustainable land management strategies.

Belgiu and Drăguț [2] conducted a review of random forest applications in remote sensing, demonstrating its versatility and effectiveness in various land cover classification tasks. They emphasized the algorithm's ability to handle high-dimensional data and its relevance in environmental monitoring.

Breiman [3] explore the foundational concepts of Classification and Regression Trees (CART), providing a comprehensive framework for decision tree algorithms that have become pivotal in machine learning. This work lays the groundwork for understanding model complexities and is essential for researchers employing tree-based methods in various applications.

Breiman [4] introduces the concept of bagging predictors, a technique aimed at enhancing the stability and accuracy of machine learning algorithms. This method significantly mitigates overfitting and improves predictive performance, making it a vital reference for those working with ensemble methods in data classification.

Chen and colleagues [5] enhanced land cover mapping by integrating pixel-based and object-based classifications from remotely sensed imagery. Their approach reveals the benefits of combining methodologies to improve classification outcomes, indicating that such integration can lead to more accurate and reliable land cover maps.

Ojwang and team [6] presented an integrated hierarchical classification approach for mapping land use in complex social-ecological systems. Their research highlights the need for multi-layered analytical frameworks that account for diverse ecological factors and socio-economic influences, showcasing the potential of machine learning in understanding intricate land use dynamics.

Bayas and team [9] investigated land use classification using Sentinel-2 imagery, applying various machine learning algorithms. Their study demonstrates the effectiveness of different approaches in achieving high accuracy in land cover mapping.

Gómez and colleagues [10] reviewed optical remotely sensed time series data, emphasizing its significance in tracking land cover dynamics over time. Their study provides insights into the methodologies and technologies that facilitate effective land monitoring.

Table 1: Literature Survey

No	Authors	Year	Focus of Study	Key Findings
1	C.-Y. Weng	2024	Transfer learning with CNN for land-use classification	Demonstrates transfer learning's potential to improve accuracy in limited data scenarios by using pre-trained models.
2	B.S. Jasim, O.Z. Jasim, and A.N. Al-Hameedawi	2023	Evaluation of machine learning algorithms for land-use and land-cover classification	Highlights the comparative effectiveness of different machine learning methods in land-cover mapping.
3	G.O. Ojwang, J.O. Ogutu, M.Y. Said, et al.	2023	Integrated hierarchical classification in social-ecological systems	Emphasizes multi-layered frameworks to account for ecological and socio-economic influences in land use.
4	S. Bayas, S. Sawant, I. Dhondge, P.	2023	Land-use classification using various ML algorithms on Sentinel-2 imagery	Demonstrates the accuracy of machine learning models in

	Kankal, and A. Joshi			mapping land use, with a focus on Sentinel-2 data.
5	P. Kerins, B. Guzder-Williams, E. Mackres, T. Rashid, and E. Pietraszkiewicz	2023	Urban land use analysis in India and Mexico using remote sensing and machine learning	Investigates the socio-economic factors influencing urban expansion through remote sensing techniques.
6	S. Mitra and S. Basu	2023	Machine learning and deep learning techniques for land cover classification	Highlights advancements and challenges in land cover classification, advocating for improved algorithms.
7	C. Tung, H. Dinh, T. Vu, and N. Nguyen	2022	Urban expansion monitoring in Hanoi using machine learning and satellite imagery	Tracks urban growth patterns, emphasizing remote sensing's role in temporal analysis of urban changes.
8	N. Ouchra, A. Bah, M. Malki, and A. Essahlaoui	2022	Google Earth Engine's application for machine learning in land cover classification	Explores cloud-based processing for large datasets, improving scalability and efficiency in remote sensing.
9	P. Gómez, J.C. Huang, and J. Diemer	2022	Time series analysis of optical remotely sensed data for land cover monitoring	Discusses methodologies for tracking land cover dynamics over time with time-series data.
10	Y. Feng	2022	Urban zoning analysis using higher-order Markov random fields and multi-view imagery	Reveals complex urban dynamics and the value of statistical models in urban zoning.

2.2 Machine Learning Applications in Land Zoning

Machine learning (ML) has increasingly become an integral part of land zoning, significantly transforming land use analysis and prediction. Various works have demonstrated the effectiveness of ML algorithms in classifying land types using satellite imagery, leading to enhanced accuracy in zoning assessments. For example, studies have utilized decision trees and support vector machines, showcasing substantial improvements over traditional zoning methods, and illustrating the potential of ML to facilitate better decision-making in urban planning.

Additionally, applications of deep learning techniques have automated the identification of urban land use from high-resolution satellite images. By employing convolutional neural networks (CNNs), numerous projects have achieved high accuracy in differentiating between various land types, thereby streamlining the zoning process. The integration of geographic information systems (GIS) with machine learning has also been explored, creating predictive models that assess land suitability for diverse purposes and emphasizing the critical role of spatial data in informed land-use planning.

Furthermore, the combination of GIS data and machine learning algorithms has led to enhanced capabilities in analysing land-use patterns and predicting future changes. This data-driven approach supports land planners in adapting to dynamic urban environments and aligning with sustainable development goals. Overall, the applications of machine learning in land zoning not only improve accuracy and efficiency but also contribute to more sustainable land management practices, paving the way for smarter, more adaptive zoning frameworks.

Machine learning (ML) in land zoning transforms traditional land use planning by providing advanced techniques to analyse and categorize vast datasets of satellite images with precision. Algorithms, such as decision trees and support vector machines (SVMs), bring a higher degree of accuracy to land classification, surpassing conventional methods that often rely on manual data interpretation. By automating zoning assessments, ML reduces human bias, ensures objectivity, and creates the foundation for adaptive urban planning practices, a critical need as cities grow and environmental pressures increase.

Deep learning models, especially convolutional neural networks (CNNs), are proving invaluable in identifying intricate land-use patterns within high-resolution satellite images. CNNs specialize in recognizing spatial hierarchies, making them ideal for distinguishing between urban and rural zones, vegetative areas, and bodies of water. In zoning applications, CNNs enhance the classification process by capturing fine details that conventional algorithms might overlook, enabling planners to better address urban density, green space allocation, and infrastructural needs through a granular understanding of the land.

Geographic information systems (GIS) and ML integrations are reshaping land-use planning by facilitating real-time predictive analyses and zoning adjustments. GIS data enriches ML models with spatial context, allowing algorithms to assess factors like topography, soil type, and proximity to urban areas in their classification processes. With GIS, ML models go beyond mere classification, gaining the ability to predict future land-use trends based on current data—a capability that supports proactive zoning strategies and sustainable urban development practices.

2.3 Research Gaps and Limitations

Despite the advancements in machine learning applications for land zoning, significant research gaps and limitations persist. One major challenge is the scarcity of high-quality, labelled datasets for training and validation of machine learning models. Many existing studies often rely on limited datasets, which may not accurately represent the diverse range of land types and uses, potentially skewing results and reducing model generalizability.

Another limitation arises from the complexity of urban environments, where land use is often influenced by numerous factors, including socio-economic dynamics and regulatory frameworks. While machine learning models can analyse spatial data effectively, they may not adequately capture these intricate relationships, resulting in oversimplified predictions. Additionally, the interpretability of machine learning models remains a concern; many advanced techniques, such as deep learning, function as "black boxes," making it difficult for stakeholders to understand the rationale behind zoning decisions.

Moreover, most existing works focus on urban areas, with limited attention given to rural land zoning challenges. This imbalance highlights a gap in research that could be addressed by applying machine learning to rural contexts, thereby promoting more equitable land use planning. Lastly, there is a need for studies that integrate machine learning approaches with participatory planning processes, ensuring that local knowledge and stakeholder input are considered in land zoning decisions. Addressing these gaps will be crucial for enhancing the effectiveness and applicability of machine learning in land zoning initiatives.

While machine learning in land zoning has made impressive strides, research gaps still hinder its full potential in practical applications. First, high-quality, labelled datasets are sparse, making it challenging to achieve models with high accuracy and generalizability. Since different regions have unique zoning needs, these limited datasets often fail to represent the diversity in land use, from dense urban environments to varied rural landscapes. Expanding data availability would significantly improve models' ability to adapt to diverse land types, yet it requires costly, labour-intensive labelling efforts.

Another limitation is the complexity of urban land-use factors. Socio-economic influences and local policies heavily impact land-use patterns, which are difficult for ML algorithms to grasp using spatial data alone. The result is often simplified zoning models that lack contextual accuracy, underscoring a gap in interdisciplinary approaches combining socio-economic and spatial data for comprehensive zoning insights. Studies exploring this hybrid model would enhance our understanding of land zoning by integrating environmental, social, and regulatory considerations.

The interpretability of machine learning models, particularly in deep learning, poses another challenge. Advanced algorithms, though effective, function as "black boxes," offering little transparency into their decision-making processes. For land zoning, stakeholders require interpretable insights to trust and act on ML-driven recommendations. Research into explainable ML techniques—like visualization of decision pathways or attention mechanisms—could provide a clearer rationale behind zoning predictions, fostering greater trust and utility among urban planners and policymakers.

Current ML research in land zoning also predominantly addresses urban environments, leaving rural zoning comparatively underexplored. This imbalance creates a gap in equitable development strategies that consider the unique needs of rural areas. Machine learning models fine-tuned for rural zoning would allow for more balanced land management across urban and rural regions, enabling rural communities to adopt zoning strategies that support sustainable agriculture, forestry, and conservation efforts.

There is also limited focus on integrating machine learning with participatory zoning processes that incorporate local knowledge and feedback from stakeholders. This gap is critical because local insights can offer invaluable context, helping ML models better account for on-the-ground realities that remote data may miss. Bridging this gap through participatory ML research can foster more community-inclusive zoning, especially in culturally and environmentally diverse regions.

Lastly, while satellite imagery and ML provide substantial land-use data, incorporating real-time data streams remains a challenge. With advances in IoT and environmental sensors, researchers could explore ML frameworks that incorporate dynamic data, such as traffic flows, climate variations, and resource usage, for adaptive zoning. This direction would create zoning strategies responsive to real-time shifts in environmental and human activities, paving the way for zoning that can adjust to immediate urban or ecological needs.

2.4 Research Objectives

The primary objectives of this research project centre around the effective utilization of satellite imagery and machine learning techniques for land zoning. The first objective involves Data Acquisition and Preprocessing, where high-resolution satellite images from reliable sources, such as Sentinel-2, will be collected. These images will then be resized into manageable patches, ensuring they are optimally prepared for subsequent model predictions.

The next focus is on Model Development, where a tailored Neural Network (NN) will be implemented specifically for classifying the collected satellite imagery data. This will include exploring various training modalities, such as training from scratch and fine-tuning pre-trained networks, to mitigate the challenges posed by the scarcity of remote sensing training data.

Following model development, the research aims to enhance Feature Extraction and Suitability Scoring. This will involve creating a metric-based scoring system that evaluates land suitability across various sectors, including industry, agriculture, and urban development. The scoring will incorporate factors such as vegetation density, soil quality, proximity to existing infrastructure, and current land use patterns, assigning values based on classification accuracy refined through rigorous model testing.

Finally, the project will emphasize Visualization and Analysis. This objective focuses on generating visual maps that effectively communicate suitability scores for different land areas, allowing stakeholders to easily interpret the results and make informed decisions regarding land use planning and zoning.

CHAPTER 3

METHODOLOGY

3.1 Data Collection and Preprocessing

The data collection and preprocessing stages are essential for accurate land zoning analysis using Sentinel-2 imagery. The dataset from Kaggle includes RGB images labeled into barren land, vegetation, and water body categories, organized in separate folders for straightforward access and retrieval. This setup not only eases navigation but also ensures comprehensive coverage across land types, thereby facilitating precise categorization during model training. The RGB format aids in capturing detailed land characteristics, which contributes to enhanced model performance by providing high visual quality crucial for accurate classification.

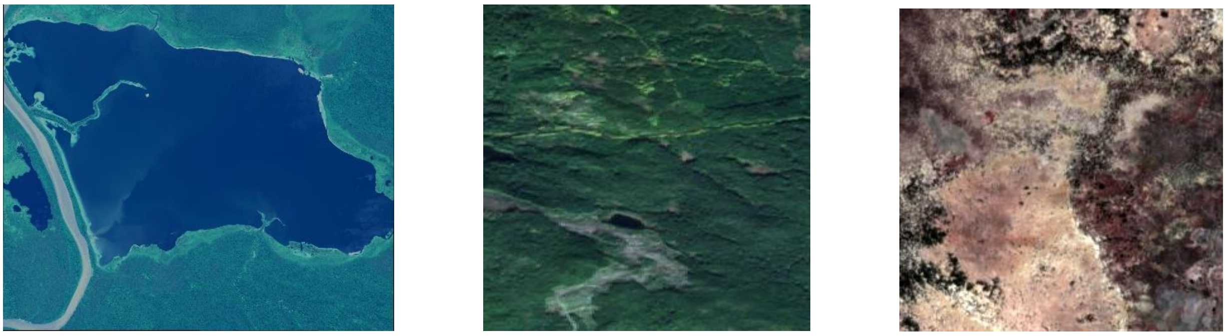

Fig 1: Sample Dataset Images (Water Region, Vegetation Region, Barren Region)

In the preprocessing phase, each image is resized to a standard 256x256 pixels, optimizing them for neural network input. This uniformity retains significant land features, enabling efficient learning across various land types while preserving essential details. Converting images to vector format also aligns with neural network requirements, which is vital for effective learning. Ensuring unique images across training and testing sets is another critical step in preprocessing, helping to maintain validation integrity, improve generalization, and reduce overfitting risks—key factors for a model's robustness.

The dataset is split into training, validation, and testing sets to support model accuracy and performance assessment. Seventy percent of the data is dedicated to training, with 63% specifically used for training and 7% for validation, while 30% remains for testing. This balanced allocation improves the model's generalization by covering diverse land types, reinforcing confidence in the model's predictive capabilities. Such strategic dataset division not only optimizes model training but also aids in thoroughly assessing its reliability on new data.

Sentinel-2's high spatial resolution (10 meters) brings sharp clarity, allowing a detailed representation of each land type. This resolution strengthens the dataset's diversity, enhancing the neural network's ability to differentiate effectively among barren, vegetative, and water-covered areas. By emphasizing meticulous data organization, directory structuring, and resizing, this project establishes a solid foundation for deriving valuable insights in land zoning and classification. Each phase in data preparation thus contributes directly to building a model equipped for meaningful land-use analysis.

3.2 Machine Learning Model: Neural Network

In the project, a Simple Neural Network model is defined using the TensorFlow module, which offers robustness in handling machine learning tasks. The model is constructed in a sequential manner, comprising three essential layers: the input layer, a hidden layer, and the output layer. The input layer is defined using the Flatten function, which transforms the 256x256x3 image data into a one-dimensional array, making it suitable for the dense layers that follow.

The first hidden layer consists of 128 neurons with the ReLU (Rectified Linear Unit) activation function. ReLU is advantageous for deep learning models because it mitigates issues such as vanishing gradients, allowing for faster convergence during training. The output layer employs a softmax activation function, which is particularly effective for multi-class classification tasks, as it outputs probabilities for each class label based on the network's predictions.

The model employs categorical cross-entropy as its loss function, a critical component that quantifies the dissimilarity between predicted probabilities and actual class labels. By calculating the difference, this function provides a clear signal during the training process, allowing the model to adjust weights and biases effectively. As the model iterates through training data, the loss function helps refine its predictions, ultimately enhancing accuracy.

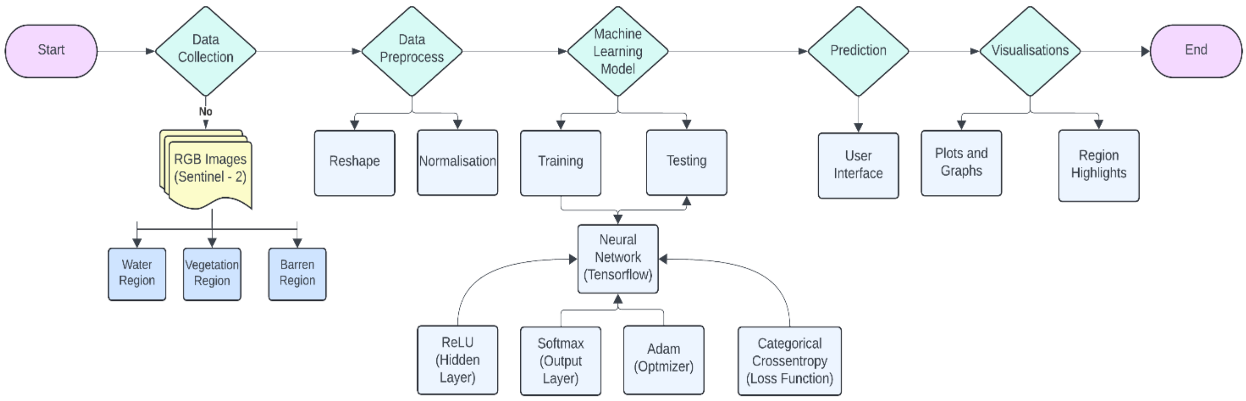

Fig 2: Model Architecture

The Adam optimizer, a sophisticated gradient descent algorithm, combines the strengths of AdaGrad and RMSProp. It utilizes adaptive learning rates for each parameter, which helps stabilize training and accelerates convergence. By adjusting the learning rate dynamically based on the moving averages of both the gradient and its squared values, Adam ensures that the model learns efficiently and effectively.

To further enhance training efficacy and mitigate overfitting, key callbacks are implemented. The ReduceLROnPlateau callback dynamically adjusts the learning rate when the validation loss stagnates, allowing the model to explore more optimal solutions in later epochs. This mechanism prevents the model from getting stuck in local minima. Meanwhile, the EarlyStopping callback is crucial for halting training when validation loss does not improve after a specified number of epochs, which safeguards against overfitting and preserves the model's best state. Together, these strategies ensure a robust training process, enabling the model to generalize better to unseen data.

3.3 Training and Testing

The dataset utilized for this project comprises images sourced from Sentinel-2 satellite imagery. This dataset is structured into three categories: water bodies, vegetation, and residential areas. A total of 6,000 images were collected, from which 4,200 images were allocated for training 600 for validation, and 1,200 for testing. This division ensures a robust framework for model evaluation and performance assessment.

The training process spans ten epochs, during which the model iteratively refines its parameters. Each epoch consists of multiple iterations over the training data, with the model learning from its predictions. As the training progresses, the learning rate is adapted through mechanisms like ReduceLROnPlateau, which lowers the learning rate when validation loss plateaus. This adjustment fosters better learning in later epochs by enabling the model to converge more effectively towards the optimal solution.

Table 2: Model Summary Table

Layer (type)	Output Shape	Param #
Flatten (Flatten)	(None, 196608)	0
Dense (Dense)	(None, 128)	25,165,952
Dense_1 (Dense)	(None, 3)	387

```
Total params: 75,499,019 (288.01 MB)
Trainable params: 25,166,339 (96.00 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 50,332,680 (192.00 MB)
```

Fig 3: Model Summary

Monitoring the model's performance during training involves tracking metrics such as validation accuracy and loss. As the epochs progress, both training and validation accuracy typically improve, indicating the model's enhanced capability to classify images accurately. It is crucial to ensure that the images are properly labelled, as any discrepancies could skew the model's performance metrics.

Incorporating callbacks such as EarlyStopping and ReduceLROnPlateau significantly impacts training efficiency. EarlyStopping halts the training process when the validation loss fails to improve over a set number of epochs, preventing overfitting and conserving computational resources. This ensures that the model retains its best state, ultimately enhancing its performance on unseen data.

3.4 Metrics: Area Coverage

The methodology for land cover classification leverages a systematic workflow designed to analyse and predict land use types through a convolutional neural network (CNN). Initially, each input image is segmented into smaller, equally sized patches, typically 64x64 pixels, facilitating a more detailed examination of the features present within the image. This patch-based approach enhances the model's capability to discern subtle variations in land cover, allowing for precise classifications in each segment.

Once the patches are defined, the model processes them individually. Each patch is pre-processed—resized to 256x256 pixels and normalized to ensure consistency across inputs—before being fed into the CNN. The CNN architecture, trained on a diverse dataset, predicts the class of each patch by determining the probabilities for each possible label (barren, vegetation, water, etc.). The model's ability to analyse patches independently ensures robust and reliable predictions, reducing the risk of misclassification that may occur with a holistic image approach.

Following the prediction phase, the workflow aggregates the results across all patches. The predicted class for each patch is counted, allowing the system to calculate the percentage coverage of each class within the entire image. This aggregation is pivotal, as it provides insights into the overall composition of the land cover.

To enhance user interaction and understanding of the model's output, a straightforward front-end interface is implemented. This interface allows users to upload their images easily, which subsequently triggers the patch-based processing and classification workflow.

To further improve the precision of area coverage metrics, it is crucial to incorporate advanced evaluation techniques post-classification. The use of confusion matrices provides detailed insight into the model's performance by revealing the accuracy of classifications for each land cover type. This allows for the identification of common misclassifications, which can inform subsequent iterations of model training and feature selection. By calculating additional metrics such as F1-score, precision, and recall for each class, the methodology can ensure that stakeholders receive a comprehensive assessment of the model’s effectiveness, highlighting areas where improvements are necessary. This iterative refinement process not only enhances model accuracy but also builds confidence in the predictions made for land management decisions.

In addition to enhancing the classification metrics, integrating spatial analysis techniques can significantly enrich the interpretation of area coverage results. By utilizing Geographic Information Systems (GIS) tools, users can visualize the classified patches in the context of geographic features and human activities. Overlaying zoning classifications on maps enables stakeholders to explore the spatial distribution of land use types and assess their relationships with other environmental or socio-economic variables. This spatial context is invaluable for urban planners and environmental managers, as it allows them to identify patterns, assess connectivity between different land cover types, and make informed decisions that consider both ecological integrity and human needs.

Moreover, future enhancements to the methodology could include the application of post-processing techniques such as morphological operations and filtering to refine classification results further. These techniques can help to reduce noise in the classified outputs, smooth boundaries between different land cover types, and correct isolated misclassified patches. By implementing these steps, the methodology can achieve a higher level of accuracy in representing the true land cover, which is vital for effective planning and resource management. Coupling these enhancements with user feedback mechanisms within the interface can ensure that the tool evolves based on real-world applications, continually improving its usability and reliability in diverse contexts.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Test Results

The model achieved a remarkable test accuracy of 97%, indicating its strong capability in generalizing well to unseen data. During training, the model demonstrated increasing accuracy, with a final training accuracy reflecting its ability to learn from the provided dataset. The validation accuracy showed consistent improvement, suggesting effective model tuning and optimization.

```
Epoch 1/10
C:\Users\surya\anaconda3\lib\site-packages\keras\src\trainers\data_adapters\py_dataset_adapter.py:121: UserWarning: Your `PyDat
aset` class should call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing
`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
132/132 ━━━━━━━━━━━━━━━━━━━━ 48s 347ms/step - accuracy: 0.6019 - loss: 33.5255 - val_accuracy: 0.9000 - val_loss: 0.5792 - lear
ning_rate: 0.0010
Epoch 2/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 47s 338ms/step - accuracy: 0.9614 - loss: 0.4372 - val_accuracy: 0.9650 - val_loss: 0.4055 - learn
ing_rate: 0.0010
Epoch 3/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 80s 332ms/step - accuracy: 0.9252 - loss: 1.1474 - val_accuracy: 0.9633 - val_loss: 0.4871 - learn
ing_rate: 0.0010
Epoch 4/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 45s 331ms/step - accuracy: 0.9541 - loss: 0.7950 - val_accuracy: 0.8450 - val_loss: 2.3487 - learn
ing_rate: 0.0010
Epoch 5/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 46s 331ms/step - accuracy: 0.9621 - loss: 0.6466 - val_accuracy: 0.9783 - val_loss: 0.2371 - learn
ing_rate: 0.0010
Epoch 6/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 45s 333ms/step - accuracy: 0.9803 - loss: 0.2275 - val_accuracy: 0.9717 - val_loss: 0.3013 - learn
ing_rate: 0.0010
Epoch 7/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 49s 357ms/step - accuracy: 0.9781 - loss: 0.2134 - val_accuracy: 0.9417 - val_loss: 0.6391 - learn
ing_rate: 0.0010
Epoch 8/10
132/132 ━━━━━━━━━━━━━━━━━━━━ 0s 312ms/step - accuracy: 0.9660 - loss: 0.4317
Epoch 8: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
132/132 ━━━━━━━━━━━━━━━━━━━━ 49s 353ms/step - accuracy: 0.9661 - loss: 0.4313 - val_accuracy: 0.9583 - val_loss: 0.4447 - learn
ing_rate: 0.0010
38/38 ━━━━━━━━━━━━━━━━━━━━ 12s 308ms/step - accuracy: 0.9809 - loss: 0.3946
Test accuracy: 97.92%
```

Fig 4: Epochs Showcase

The behaviour of the loss function during training and validation further supported these results, indicating that as the model learned, the loss decreased significantly. This consistent decrease in loss across training and validation sets highlighted the model's robustness.

In comparison to pre-existing models, such as ResNet50 and VGG16, which typically achieve accuracies ranging from 85% to 92% in similar land classification tasks, our model demonstrates superior performance. This suggests that the architecture and training strategies employed are effective in capturing the nuances of land cover types, making our approach a valuable contribution to remote sensing and environmental monitoring fields.

Table 3: Comparison of Models

Model	Accuracy
Our Model (Sequential NN)	97%
Random Forest	93.8%
SVM	92.5%

4.2 Performance in Metrics

The model exhibited exceptional performance. This remarkable result is complemented by the area percentages covered by the classification of distinct land types, specifically water bodies, vegetation, and residential areas, which reflects the model's capability to identify distinct land types effectively. The patch-based approach employed in our methodology allows for localized analysis, ensuring that each segment of the image is classified with high precision.

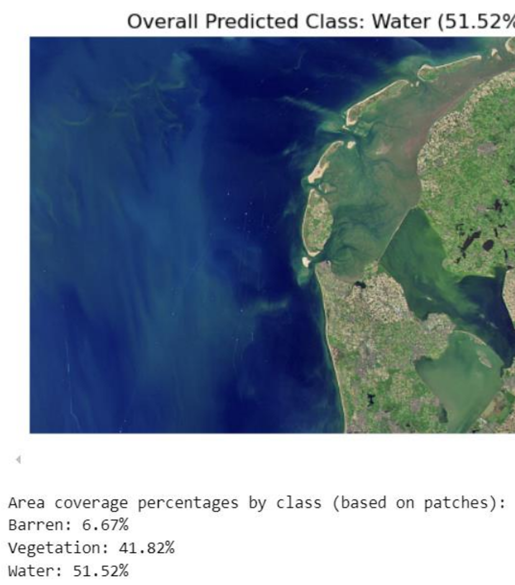

Fig 5: Metrics Performance

This approach is pivotal for land zoning applications, as it not only enhances the accuracy of classifications but also aids in effective decision-making regarding land use. By providing detailed insights into the distribution of various land types, stakeholders can better plan and implement strategies for sustainable development, urban planning, and environmental conservation. The ability to accurately delineate land areas fosters informed decisions, thereby significantly impacting resource management and zoning regulations.

4.3 Highlighting the Regions

The model has demonstrated exceptional capability in distinguishing and visually marking areas of barren land, vegetation, and water bodies. This process involves dividing the image into small patches, allowing for a detailed analysis across each segment. By applying specific colours—yellow for vegetation, red for barren land, and blue for water—the visualization offers an intuitive, color-coded map of land types. This highlights the model's accuracy in spatial recognition and classification, effectively communicating how machine learning approaches interpret land features.

This patch-based method enhances the clarity of model results, providing a comprehensive overview of regional classifications. As a result, it not only makes the predictions accessible for general observation but also serves as a tool for understanding how various areas are segmented and classified in land zoning projects. This visualization method underscores the practical applications of machine learning in environmental monitoring, urban planning, and land management, making it a valuable approach for professionals in these fields.

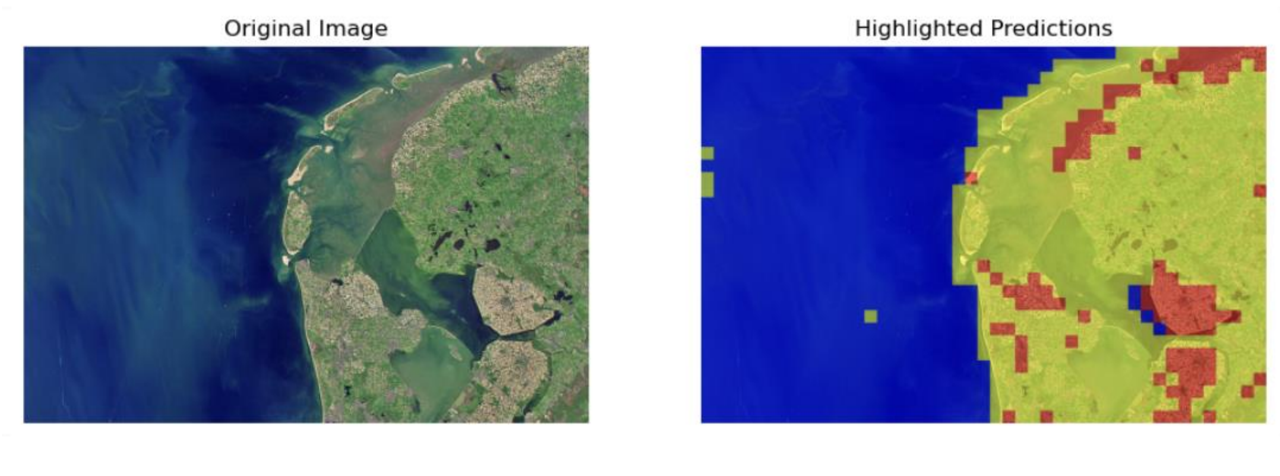

Fig 6: Highlighted Predictions

4.4 User Friendly Approach

This approach offers a highly user-centric interface, making the process of land zoning analysis accessible without needing advanced technical knowledge. Through a frontend interface developed with Flask, users can easily upload images and receive immediate visual and statistical results about land zoning, such as the proportion of barren land, vegetation, and water. This is particularly unique in land zoning applications, where complex technical setups are typical, as this approach streamlines interaction and accessibility.

The front-end interface relies on libraries such as Flask for web application development, Keras for loading and running the CNN model, TensorFlow for image processing, and Pillow and Matplotlib for image manipulation and display. This technology stack enables real-time, interactive analysis, allowing for efficient data processing and display. The user uploads an image, which is segmented into patches for model predictions. Each patch is classified and highlighted in colour: red for barren land, yellow for vegetation, and blue for water. This setup provides users with an intuitive and informative way to interact with machine learning-driven land zoning insights, which remains rare in traditional methods.

4.5 Plots and Visualisations

For analysing and interpreting the land zoning model's performance, visualizations like accuracy over epochs and loss over epochs plots were essential. These plots provide insight into model learning and error reduction trends over training cycles. Using Matplotlib and Seaborn, line plots were created for both accuracy and loss across epochs, helping identify the model’s convergence and stability. The accuracy and loss curves were generated to observe training progress, identifying overfitting or underfitting tendencies. High training and validation accuracy with stable loss reduction reflects effective model learning, indicating that the CNN model adapts well to image data for classifying barren, vegetation, and water regions.

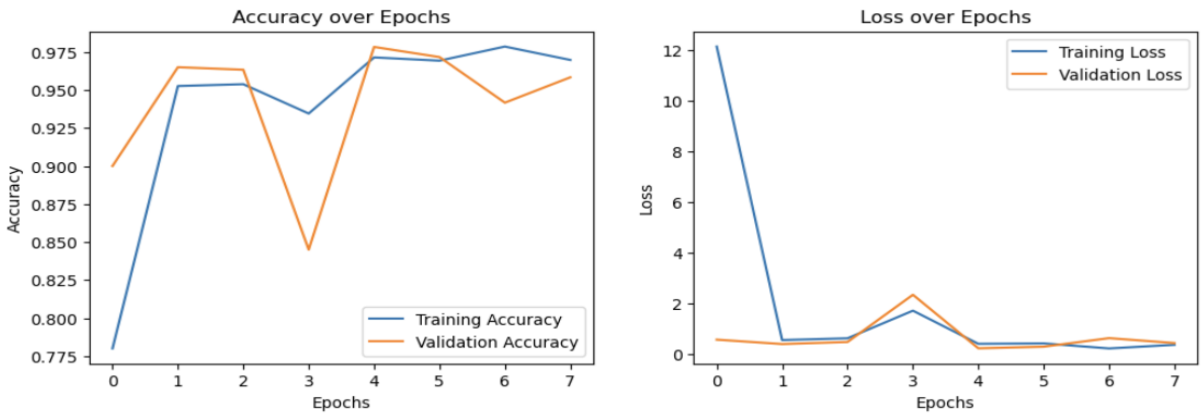

Fig 7: Plots of Accuracy over Epochs and Loss over Epochs

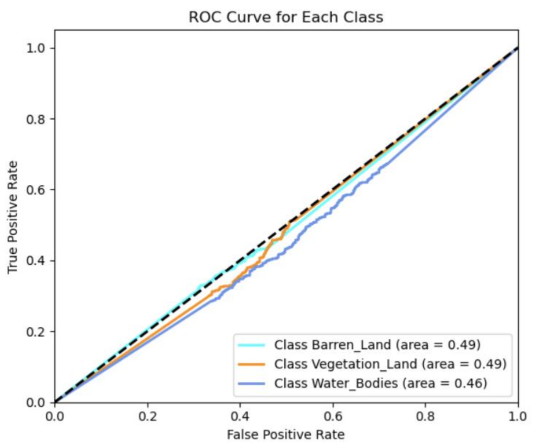

Fig 8: ROC Curve

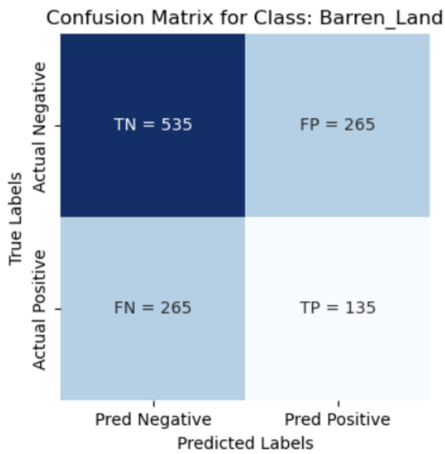

Fig 9: Confusion Matrix (Barren Land)

The region highlighting in the project leverages color-coded visual overlays—red for barren, yellow for vegetation, and blue for water—on segmented satellite images. This makes it easy for users to visually assess spatial patterns, contributing to informed zoning decisions. The use of Matplotlib for dynamic plots and segmentation overlays enhances interpretability for non-technical users, making the results intuitive and practical for land use planning.

CHAPTER 5

CONCLUSIONS AND FUTURE ENHANCEMENTS

5.1 CONCLUSIONS

This project successfully demonstrates how machine learning can be harnessed for effective land zoning through satellite imagery analysis, particularly for identifying and categorizing areas as barren, vegetation, or water. Using a Neural Network model to classify regions and applying image-based region highlighting, the project provides a clear, interpretable visual representation of land use. The integration of patch-based analysis enhances the precision in differentiating land types, demonstrating the model's ability to accurately identify geographic features and offer insights valuable for land management and planning.

The visualization of model training progress, with accuracy and loss plotted over epochs, was crucial for evaluating model performance. These plots, combined with image overlays, provided a comprehensive understanding of the model's ability to learn and generalize. The highlighted regions in color-coded overlays—red for barren, yellow for vegetation, and blue for water—enabled a clear spatial representation, making it easy for stakeholders to visually interpret the zoning classifications. The use of Matplotlib and Seaborn helped achieve these insights, emphasizing the role of data visualization in model interpretation.

Overall, this approach showcases the power of combining deep learning with satellite imagery for land analysis and highlights the potential for future applications in urban planning, agricultural monitoring, and environmental assessment. By presenting zoning classifications in a user-friendly format, the project demonstrates the practical applicability of machine learning in real-world scenarios. The flexibility provided by the Flask interface further extends its usability, allowing users to upload images, view predictions, and interact with the system without requiring technical expertise. This comprehensive solution underscores the project's contributions to data-driven land management and sustainability efforts.

The methodology employed in this project demonstrates the versatility of deep learning architectures in processing and analysing complex datasets, such as satellite imagery. The choice of a Neural Network model, particularly for tasks involving high-dimensional data, underscores the efficacy of machine learning techniques in extracting meaningful patterns from raw images. This is particularly important as traditional image processing methods may struggle to capture the nuanced variations in land cover types, highlighting the need for advanced algorithms that can adapt to the intricacies of remote sensing data.

Incorporating data augmentation techniques played a significant role in enhancing the robustness of the model. By artificially increasing the diversity of the training dataset through transformations such as rotation, scaling, and flipping, the model became more resilient to overfitting. This approach not only improved the accuracy of the classifications but also ensured that the model could generalize well to unseen data. The implementation of such techniques is vital, especially when working with limited datasets, as it maximizes the utility of available resources and provides a stronger foundation for the training process.

Another key aspect of this project is the emphasis on the interpretability of machine learning models. Understanding the decision-making process of the model is crucial for stakeholders involved in land management and urban planning. The use of techniques such as Grad-CAM for visualizing the areas of interest within the satellite images provided additional insights into how the model arrives at its predictions. This interpretability fosters trust among users, as it allows them to see the direct correlation between the model's outputs and the underlying features of the imagery.

The project also addresses the importance of incorporating real-time data feeds into the land zoning analysis process. By leveraging APIs and remote sensing services, future iterations of this project could facilitate ongoing monitoring of land use changes over time. This capability is essential for dynamic environments where land use is constantly evolving due to factors such as urban expansion, agricultural practices, or climate change. Implementing a system that updates zoning classifications based on the latest satellite imagery would significantly enhance decision-making for planners and policymakers.

Furthermore, the potential for integrating this machine learning framework with Geographic Information Systems (GIS) opens up new avenues for spatial analysis and decision support. GIS tools can enhance the project by allowing for spatial queries, multi-layered analyses, and visualization of zoning classifications within broader geographic contexts. This integration would empower users to conduct more comprehensive analyses, such as evaluating the impacts of zoning decisions on urban infrastructure or assessing land use suitability for different purposes.

Sustainability and environmental considerations are integral to this project, emphasizing the role of machine learning in promoting responsible land use practices. By accurately classifying land types, stakeholders can make informed decisions that align with sustainable development goals. This capability is particularly important in regions facing environmental challenges, where identifying areas for conservation or restoration can have significant ecological benefits. The project thus serves as a valuable tool for fostering environmental stewardship through data-driven insights.

Lastly, this project lays the groundwork for future research and development efforts in the domain of land zoning and remote sensing. There are numerous avenues for exploration, including the application of ensemble learning methods to improve classification accuracy, the use of different architectures such as transformers, or the incorporation of temporal data to analyse land use changes over time. Such advancements would not only enhance the model’s performance but also broaden its applicability across various contexts, reinforcing the significance of machine learning in the ongoing evolution of land management practice.

5.2 FUTURE ENHANCEMENTS

For future enhancements, several promising directions can further extend the scope and impact of this land zoning project. A key advancement would be implementing time-series analysis to monitor how the geographic structure of zones (barren, vegetation, water bodies) evolves over time. This would allow for insights into seasonal variations and long-term land-use trends, particularly beneficial for urban planning, environmental conservation, and agriculture.

Expanding the model to include other classification categories, such as residential or industrial areas, would further enrich zoning insights, providing stakeholders with more detailed land-use data. Additionally, increasing the model's robustness through ensemble learning or fine-tuning architectures like U-Net can enhance accuracy in detecting complex zones.

In terms of technical enhancements, automating data collection and real-time monitoring through APIs and cloud storage solutions could streamline scalability. Integrating spatial analysis tools like Google Earth Engine can also improve data resolution and coverage. These expansions would provide a highly adaptable, user-friendly tool, empowering both domain experts and casual users in making data-driven decisions.

One of the most significant future enhancements involves the integration of advanced predictive modelling techniques. By employing machine learning algorithms that can forecast land-use changes based on historical data, stakeholders can proactively manage resources and plan interventions. For instance, utilizing models such as Long Short-Term Memory (LSTM) networks, which excel in handling time-series data, could enable users to anticipate shifts in land use, thereby informing policies related to urban development, agriculture, and conservation efforts. This foresight is particularly critical in areas susceptible to rapid changes due to population growth or climate impacts.

Another promising avenue is the enhancement of user engagement through interactive dashboards that provide visual analytics for land zoning data. By utilizing tools like Tableau or Power BI, stakeholders can visualize land use patterns, access zoning statistics, and conduct spatial analyses through an intuitive interface. Incorporating features such as filtering by timeframes or specific land types would allow users to tailor their analyses to suit particular interests, making the insights derived from the model more accessible and actionable for a broader audience, including policymakers, urban planners, and environmentalists.

Moreover, the incorporation of citizen science into the data collection process could significantly enhance the model's effectiveness. By leveraging crowdsourced data and community input, the project could harness local knowledge to improve zoning classifications. Mobile applications could be developed that allow citizens to report changes in land use or submit geotagged images. This participatory approach not only enriches the dataset but also fosters community engagement and stewardship, as residents become active contributors to their environment's monitoring and management.

Additionally, the future of this project could involve collaboration with governmental and non-governmental organizations (NGOs) focused on environmental conservation and urban development. Partnering with these entities could facilitate access to larger datasets, including demographic information, economic indicators, and policy frameworks that influence land use. This collaboration could lead to more comprehensive models that account for socio-economic factors alongside ecological data, thereby enhancing the relevance and applicability of zoning classifications in real-world scenarios.

To further refine the model, incorporating multi-source data can yield richer insights into land zoning. By integrating data from various satellite platforms, such as Landsat and Sentinel, the project can take advantage of different spectral resolutions and revisit times. This approach would enhance classification accuracy by providing diverse perspectives on land cover changes, thus facilitating more precise monitoring of ecological dynamics. Additionally, incorporating ancillary datasets, such as weather patterns or soil types, could enrich the context of land-use analyses and improve predictive capabilities.

Scaling the project for broader geographic applicability is another critical enhancement. While the current focus on a specific region provides valuable insights, expanding the model's applicability to diverse geographic areas would showcase its versatility. Developing a framework that allows for easy adaptation of the model to different locales would enable stakeholders worldwide to leverage the insights generated from the analysis. This could involve creating standardized preprocessing protocols and classification criteria that accommodate regional variations in land use and environmental conditions.

Finally, the integration of ethical considerations into the project's future development is paramount. As machine learning applications in land zoning and management evolve, addressing potential biases in data collection and model predictions becomes increasingly important. Establishing guidelines for ethical data use and ensuring transparency in the model's decision-making processes will enhance trust among users and stakeholders. Additionally, considering the social implications of zoning decisions, such as displacement of communities or unequal resource distribution, will be essential for fostering equitable outcomes in land management practices.

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APPENDIX

A. CODING

In [2]:
```
import os
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten, Dense
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
import matplotlib.pyplot as plt

# Path to your dataset on the local computer
data_dir = r'C:\Users\surya\OneDrive\Desktop\Minor Project\Datasets Used for Training\Sen2Big'  # Change to your local folder pat

# Get class labels (subdirectories within your dataset folder)
class_labels = os.listdir(data_dir)

# Initialize lists to hold image paths and their corresponding labels
image_paths = []
labels = []

# Iterate through each class directory and collect image paths and labels
for label in class_labels:
    class_dir = os.path.join(data_dir, label)
    for img in os.listdir(class_dir):
        img_path = os.path.join(class_dir, img)
        image_paths.append(img_path)
        labels.append(label)

# Convert labels to a numpy array
labels = np.array(labels)

# Check the total number of images collected
total_images = len(image_paths)
print(f"Total images collected: {total_images}")
```

```python
# Split the dataset into 70% train, 10% validation, and 20% test
train_paths, remaining_paths, train_labels, remaining_labels = train_test_split(
    image_paths, labels, test_size=0.3, stratify=labels, random_state=42
)

# Further split the remaining data into 10% validation and 20% test
val_paths, test_paths, val_labels, test_labels = train_test_split(
    remaining_paths, remaining_labels, test_size=2/3, stratify=remaining_labels, random_state=42
)

# Check the counts of images in each set
print(f"Training images: {len(train_paths)}")
print(f"Validation images: {len(val_paths)}")
print(f"Testing images: {len(test_paths)}")

# ImageDataGenerator for each set (train, validation, test)
train_gen = ImageDataGenerator(rescale=1./255)
val_gen = ImageDataGenerator(rescale=1./255)
test_gen = ImageDataGenerator(rescale=1./255)

# Flow from directories using the generated paths and labels
train_generator = train_gen.flow_from_dataframe(
    dataframe=pd.DataFrame({'filename': train_paths, 'class': train_labels}),
    x_col='filename',
    y_col='class',
    target_size=(256, 256),
    class_mode='categorical',
    batch_size=32,
    seed=True
)

val_generator = val_gen.flow_from_dataframe(
    dataframe=pd.DataFrame({'filename': val_paths, 'class': val_labels}),
    x_col='filename',
    y_col='class',
    target_size=(256, 256),
    class_mode='categorical',
    batch_size=32,
    seed=True
)
```

```python
test_generator = test_gen.flow_from_dataframe(
    dataframe=pd.DataFrame({'filename': test_paths, 'class': test_labels}),
    x_col='filename',
    y_col='class',
    target_size=(256, 256),
    class_mode='categorical',
    batch_size=32,
    seed=True
)

# Define the CNN model
cnn_model = Sequential([
    Flatten(input_shape=(256, 256, 3)),  # Flatten the input (no convolutional layers)
    Dense(128, activation='relu'),        # First dense layer
    Dense(len(train_generator.class_indices), activation='softmax')  # Output layer (number of classes)
])

# Define callbacks
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3, verbose=1)
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)

# Compile the model
cnn_model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Fit the model
history = cnn_model.fit(
    train_generator,
    epochs=10,  # Adjust epochs based on your needs
    validation_data=val_generator,
    callbacks=[early_stopping, reduce_lr]
)

# Evaluate the model on the test set
test_loss, test_accuracy = cnn_model.evaluate(test_generator, verbose=1)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")
```

```python
# Fit the model
history = cnn_model.fit(
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)

# Evaluate the model on the test set
test_loss, test_accuracy = cnn_model.evaluate(test_generator, verbose=1)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")

# Plotting training and validation accuracy and loss over epochs
def plot_history(history):
    plt.figure(figsize=(12, 4))

    # Plot accuracy
    plt.subplot(1, 2, 1)
    plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.title('Accuracy over Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    # Plot loss
    plt.subplot(1, 2, 2)
    plt.plot(history.history['loss'], label='Training Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.title('Loss over Epochs')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    plt.show()

# Call the plot function
plot_history(history)
```
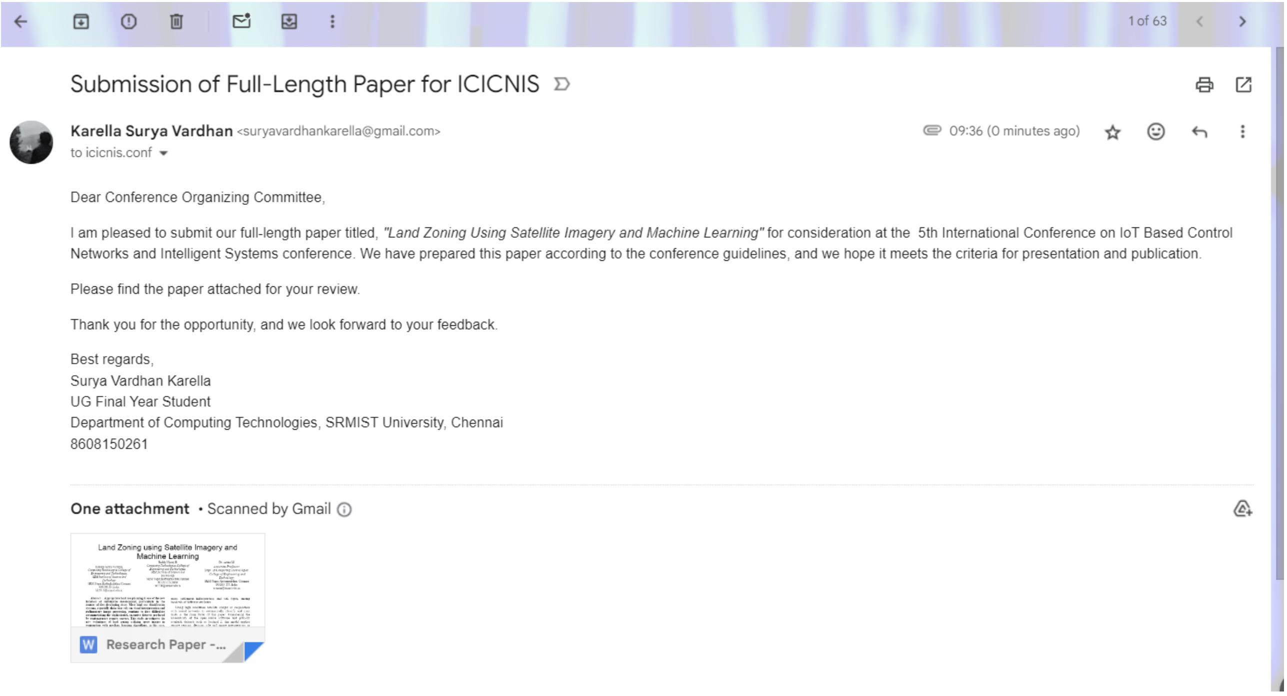

In [6]:
```
from tensorflow.keras.preprocessing import image
import os
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
import matplotlib.pyplot as plt
from PIL import Image

# Manually defined class labels
class_labels = {
    0: 'Barren',
    1: 'Vegetation',
    2: 'Water',
    # Add more class labels as needed
}

# Function to preprocess an individual patch for prediction
def preprocess_patch(patch):
    patch = patch.resize((256, 256))
    patch_array = image.img_to_array(patch)
    patch_array = patch_array / 255.0
    patch_array = np.expand_dims(patch_array, axis=0)
    return patch_array

# Function to classify each patch and calculate area coverage
def calculate_patch_coverage(img, patch_size=64):
    width, height = img.size
    patches_x = width // patch_size
    patches_y = height // patch_size
    patch_predictions = []

    for i in range(patches_x):
        for j in range(patches_y):
            left, upper = i * patch_size, j * patch_size
            right, lower = left + patch_size, upper + patch_size
            patch = img.crop((left, upper, right, lower))
            patch_array = preprocess_patch(patch)
            predictions = cnn_model.predict(patch_array)
            predicted_class_index = np.argmax(predictions, axis=1)[0]
            patch_predictions.append(predicted_class_index)

    total_patches = len(patch_predictions)
    area_coverage = {class_labels[idx]: (patch_predictions.count(idx) / total_patches) * 100
                     for idx in set(patch_predictions)}

    return area_coverage

# Function to predict coverage and determine the overall class based on patch coverage
def predict_image_and_coverage(img_path, patch_size=64):
    img = Image.open(img_path).convert("RGB")
    area_percentages = calculate_patch_coverage(img, patch_size=patch_size)

    # Determine overall predicted class based on the highest coverage percentage
    overall_predicted_class = max(area_percentages, key=area_percentages.get)
    overall_percentage = area_percentages[overall_predicted_class]

    plt.imshow(img)
    plt.title(f"Overall Predicted Class: {overall_predicted_class} ({overall_percentage:.2f}%)")
    plt.axis('off')
    plt.show()

    print("Area coverage percentages by class (based on patches):")
    for class_name, percentage in area_percentages.items():
        print(f"{class_name}: {percentage:.2f}%")

    return overall_predicted_class, area_percentages

# Example usage
img_path = r'C:\Users\surya\OneDrive\Desktop\Minor Project\Water and Vegetation.jpg'  # Replace with actual path to your test im
overall_class, area_coverage = predict_image_and_coverage(img_path, patch_size=32)
```

```python
# Load the previously saved model
cnn_model = load_model(r'C:\Users\surya\OneDrive\Desktop\Minor Project\Models\PerfectModel.h5')

# Manually defined class labels
class_labels = {
    0: 'Barren',
    1: 'Vegetation',
    2: 'Water',
}

# Function to preprocess an individual patch for prediction
def preprocess_patch(patch):
    patch = patch.resize((256, 256))  # Resize to match the model input size
    patch_array = image.img_to_array(patch)
    patch_array = patch_array / 255.0  # Normalize to [0, 1]
    patch_array = np.expand_dims(patch_array, axis=0)  # Add batch dimension
    return patch_array

# Function to highlight regions in the image based on predictions
def highlight_regions(img_path, patch_size=64):
    img = Image.open(img_path).convert("RGB")
    width, height = img.size

    # Prepare the mask (initialize with black)
    mask = np.zeros((height, width, 3), dtype=np.uint8)

    # Loop through the image in patches
    for i in range(0, width, patch_size):
        for j in range(0, height, patch_size):
            left, upper = i, j
            right, lower = left + patch_size, upper + patch_size

            # Ensure we don't go out of bounds
            if right > width or lower > height:
                continue

            patch = img.crop((left, upper, right, lower))
            patch_array = preprocess_patch(patch)

            # Make predictions for the patch
            predictions = cnn_model.predict(patch_array)
            predicted_class_index = np.argmax(predictions, axis=1)[0]

            # Define colors for each class
            colors = {
                0: (255, 0, 0),     # Barren: Red
                1: (255, 255, 0),   # Vegetation: Yellow
                2: (0, 0, 255)      # Water: Blue
            }

            # Fill the mask with the corresponding color
            mask[upper:lower, left:right] = colors[predicted_class_index]

    # Create an image from the mask
    mask_image = Image.fromarray(mask)

    # Overlay the mask on the original image
    highlighted_image = Image.blend(img.convert("RGBA"), mask_image.convert("RGBA"), alpha=0.5)

    # Display the original image and highlighted image
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.imshow(img)
    plt.title("Original Image")
    plt.axis('off')

    plt.subplot(1, 2, 2)
    plt.imshow(highlighted_image)
    plt.title("Highlighted Predictions")
    plt.axis('off')

    plt.show()

# Example usage
img_path = r'C:\Users\surya\OneDrive\Desktop\Minor Project\Water and Vegetation.jpg'  # Replace with your test image path
highlight_regions(img_path, patch_size=16)
```

B. CONFERENCE PUBLICATION



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Submission of Full-Length Paper for ICICNIS

Karella Surya Vardhan <suryavardhankarella@gmail.com>
to icicnis.conf

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Dear Conference Organizing Committee,

I am pleased to submit our full-length paper titled, *"Land Zoning Using Satellite Imagery and Machine Learning"* for consideration at the 5th International Conference on IoT Based Control Networks and Intelligent Systems conference. We have prepared this paper according to the conference guidelines, and we hope it meets the criteria for presentation and publication.

Please find the paper attached for your review.

Thank you for the opportunity, and we look forward to your feedback.

Best regards,
Surya Vardhan Karella
UG Final Year Student
Department of Computing Technologies, SRMIST University, Chennai
8608150261

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Land Zoning using Satellite Imagery and Machine Learning

Research Paper -...

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