Fusion Based Classification of Irregular Land Parcels Using Explainable AI

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***Abstract*—Accurate identification of land types is essential for managing natural resources, planning agricultural activities, monitoring environmental changes, and supporting urban development. Traditional approaches depend heavily on visual inspection of satellite and aerial imagery, making the process slow, inconsistent, and difficult to scale for large or diverse geographic areas. To address these challenges, this work introduces an automated land-type classification framework that combines machine learning and deep learning techniques. The system primarily uses a Convolutional Neural Network (CNN) to learn spatial and textural patterns directly from images, while classical models such as Support Vector Machine (SVM) and Random Forest (RF) are used as comparative baselines. The dataset consists of satellite image tiles representing multiple land categories including vegetation, water bodies, barren soil, agricultural regions, and built-up areas. Images undergo essential preprocessing steps such as resizing, normalization, noise reduction, and illumination correction before training. Experimental analysis shows that the CNN outperforms traditional models by effectively distinguishing visually similar terrain and learning richer spatial features. The proposed framework offers a scalable and reliable solution for automated land-type mapping and can support future real-time geospatial analysis in environmental, agricultural, and urban applications. Index Term- Land classification, irregular land parcels, remote sensing, satellite imagery, Convolutional Neural Network (CNN), machine learning, Support Vector Machine (SVM), Random Forest (RF), image preprocessing, feature extraction, environmental monitoring, geospatial analysis.**

***Index Terms*—Land Type Classification, Remote Sensing, Satellite Imagery, Image Preprocessing, CNN Feature Extraction, Support Vector Machine (SVM), Random Forest (RF), Machine Learning, Deep Learning, Environmental Monitoring.**

I. INTRODUCTION

The rapid development of remote sensing technologies and the increasing availability of high-resolution satellite and aerial imagery have made land-use and land-cover classification essential for environmental monitoring, agricultural planning, disaster management, and urban development. However, the complexity of real-world landscapes characterized by irregular land parcels, mixed vegetation patterns, seasonal variability, and heterogeneous terrain makes manual image interpretation inefficient, subjective, and difficult to scale.

Traditional classification methods such as visual inspection, threshold-based rules, and pixel-level mapping often fail to accurately differentiate diverse land categories and struggle to produce consistent results. Classical machine-learning models like Support Vector Machine (SVM) and Random Forest (RF) rely heavily on handcrafted features, limiting their ability to handle complex spatial textures, spectral variations, and noisy image conditions.

Deep learning, particularly Convolutional Neural Networks (CNNs), offers a powerful solution by automatically learning hierarchical spatial and textural features from remote-sensing imagery. CNNs enable robust identification of land types such as vegetation, water bodies, urban regions, and barren surfaces with significantly improved accuracy. Motivated by these advantages, this work proposes a CNN-based land-classification model and evaluates its performance against traditional SVM and RF approaches.

1.1. Information about Author

1. Self-Attention and Fusion-Based Classification

Albarakati et al. proposed a deep learning architecture that integrates self-attention mechanisms with feature fusion to improve classification of agricultural land and general land-cover categories. Their model is capable of capturing long-range spatial dependencies in satellite images, which enhances its ability to separate visually similar areas. While the approach yields high accuracy, it requires substantial computational resources because of its complex network structure. This makes it less suitable for lightweight or real-time applications unless adequate hardware is available.

2. Multidimensional Feature Fusion with Superpixel Segmentation

Huang and colleagues introduced an object-based urban land-cover classification system that uses superpixel segmentation combined with multiple feature types. Their method merges object-level properties, CNN-derived deep features, and spatial association features learned via Graph Convolutional Networks (GCNs). The study shows that when segmentation quality is high, classification performance improves greatly. However, the method is sensitive to segmentation parameters and requires extensive preprocessing, making it computationally demanding for large datasets.

3. High-Confidence Sample Generation for Training

Xi et al. addressed the challenge of insufficient high-quality labeled data by proposing a method that generates reliable training samples from multiple global land-cover datasets. Their technique evaluates consistency across datasets to identify trustworthy labels, which are then used to train a Random Forest classifier. Although this significantly improves classification accuracy, the system heavily depends on the availability and alignment of multiple land-cover sources.

4. Use of Classical Machine Learning Models

Traditional machine learning models like Support Vector Machine (SVM) and Random Forest (RF) have been widely used in earlier land-classification research. These models perform well when the input data consists of handcrafted features such as color histograms, texture descriptors, and spectral indices. However, their reliance on manually engineered features limits their ability to generalize across diverse landscapes. They are less effective when land regions contain irregular shapes, noisy textures, or overlapping patterns. As a result, these methods often fail to distinguish subtle differences in mixed or heterogeneous terrains.

5. Shift Toward Deep Learning Approaches

Recent studies consistently show that deep learning models outperform classical methods when dealing with high-resolution remote-sensing data. CNNs, in particular, automatically learn discriminative spatial features without requiring manual extraction. They effectively capture patterns related to vegetation density, built-up structures, water bodies, and barren surfaces. This ability to learn hierarchical representations directly from raw images has made CNNs the preferred approach for modern land-classification systems.

II. METHODOLOGY

Methodological Approach The complete workflow used in this study includes five main steps: collecting satellite images, preprocessing them, extracting features, training the models, and evaluating their performance. CNN automatically learns useful patterns from the images, such as textures and shapes, while SVM and Random Forest require handcrafted features. All models are trained using the same dataset so their performance can be compared fairly.

2.1. Dataset Description

The dataset used in this work contains image patches taken from satellite and aerial sources. These images show different types of land such as vegetation, farms, barren soil, water bodies, and built-up areas. All images naturally include changes in lighting, weather, seasons, and location. Each image tile has a correct label that tells what type of land it belongs to. The dataset keeps the original irregular shapes of land parcels so the model can learn from real-world patterns.

2.2. Data Preprocessing

Before training, the images go through several cleaning steps. Blurry or damaged images are removed, and brightness corrections are applied to reduce shadows or haze. All images are resized to the same width and height so the model can process them easily. Pixel values are normalized to a standard range to help the model learn better. Finally, each label is checked manually to make sure it is correct. Since the data is image-based, no extra text or metadata features are needed.

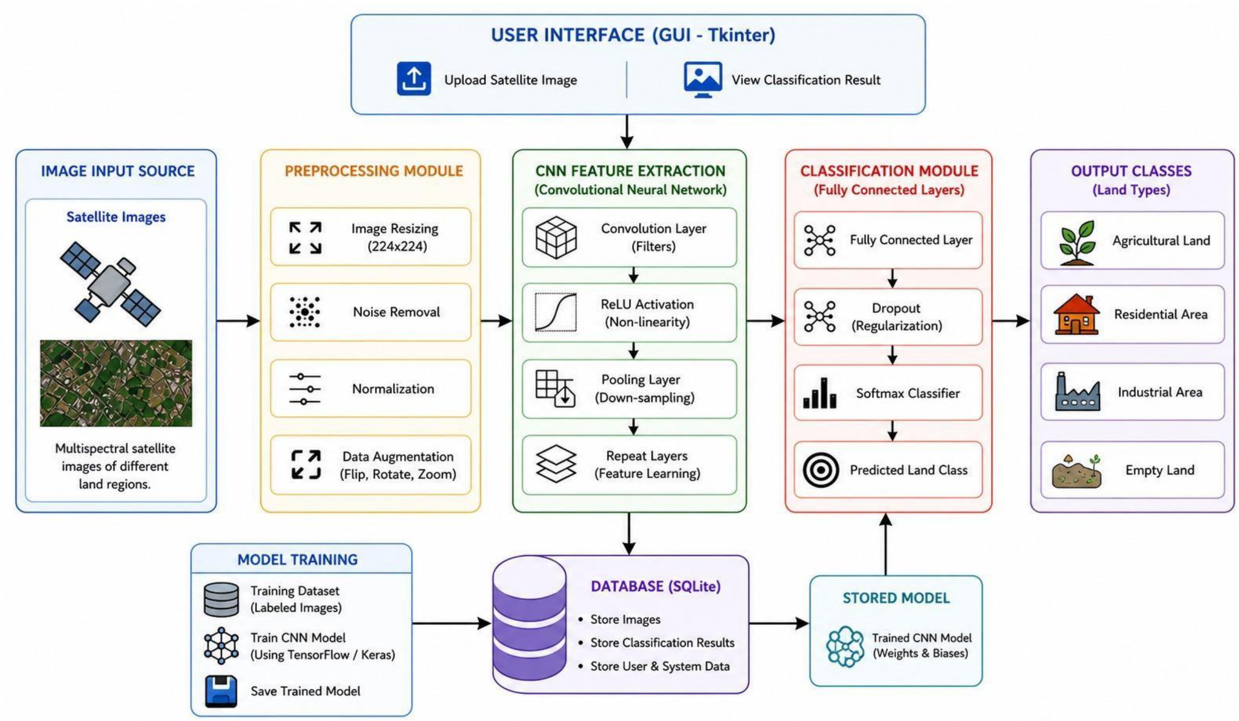

Fig. Proposed methodology and experimental setup for phishing detection using machine learning and deep learning models.

2.3. Why CNN-Based Methodology Is Used

A CNN is used because it can automatically learn important visual features without any manual work. It detects edges, textures, and shapes at different levels, making it suitable for complex and irregular land patterns. CNNs handle changes in lighting, noise, and land shapes better than traditional methods like SVM or Random Forest. This is why CNN is the main model in this study, while the other two are used for comparison.

III. PROPOSED SYSTEM

The proposed system aims to automatically classify irregular land parcels using a combination of deep learning and traditional machine learning methods to improve the accuracy and reliability of land-cover identification. The process begins with collecting satellite and aerial image tiles representing different land categories such as vegetation, water bodies, barren soil, agricultural land, and built-up regions. These images are then preprocessed through resizing, normalization, noise removal, and illumination correction to ensure consistent input quality. After preprocessing, a Convolutional Neural Network (CNN) is used as the primary model to extract meaningful spatial and textural features directly from the images, enabling the system to recognize complex patterns that traditional models may overlook. For comparison, handcrafted features are also computed and used to train Support Vector Machine (SVM) and Random Forest (RF) classifiers. All three models are trained on the same dataset, and their performance is evaluated to determine which approach handles irregular land patterns most effectively. The CNN-based approach demonstrates strong capability in learning hierarchical features and accurately distinguishing between visually similar land types, making the system suitable for practical applications such as resource management, agricultural planning, and environmental monitoring. Overall, the proposed system provides a scalable, data-driven framework that reduces manual effort and enhances the precision of land-type classification.

IV. MODEL DEVELOPMENT

The model development stage concentrates on constructing, training, and assessing multiple classification frameworks to determine the most accurate approach for land type identification using satellite and aerial imagery. This research presents a comparative analysis between deep learning–driven feature extraction using Convolutional Neural Networks (CNN) and conventional machine learning classifiers, specifically Support Vector Machine (SVM) and Random Forest (RF), which depend on manually derived features. By examining both automated feature learning and handcrafted feature-based models, the study highlights the strengths of deep spatial feature representation for managing heterogeneous land surfaces, intricate texture patterns, and mixed land-cover structures.

4.1. Convolutional Neural Network (CNN)

The proposed CNN architecture directly processes raw pixel information from land imagery to extract spatial characteristics such as edges, textures, boundaries, and color transitions. Each input image undergoes resizing and normalization before being fed through a sequence of convolution layers with ReLU activation to detect relevant patterns. Max-pooling operations progressively reduce spatial resolution while retaining dominant features. The generated feature maps are flattened and forwarded to fully connected layers that combine abstract feature representations to produce final land classification results. CNN is selected as the principal deep learning model due to its capacity to automatically learn hierarchical features without relying on predefined descriptors.

4.2. Support Vector Machine (SVM)

The SVM classifier utilizes statistical feature descriptors extracted from each satellite image, including NDVI values, entropy, mean intensity, and color histogram profiles. Rather than learning spatial relationships, SVM separates land classes using a mathematically determined decision boundary. Kernel techniques such as Radial Basis Function (RBF) and polynomial kernels are employed to transform data into higher-dimensional feature space, enabling improved class separation. Although effective for structured feature sets, SVM shows limitations when dealing with high variability and complex land textures.

4.3. Random Forest

Random Forest acts as an ensemble-based model composed of numerous decision trees, each trained on randomly selected subsets of feature data. Every tree casts an independent classification vote, and the final output label is determined through majority voting. RF provides strong resistance to overfitting and performs well with diverse feature distributions, yet similar to SVM, its accuracy is restricted by the quality of manually engineered features when compared with the deep learning approach.

4.3.1. Training Configuration

To maintain consistency and avoid bias during evaluation, the dataset is split into 80’ for training and 20’ for testing, following the common practice adopted in recent remote-sensing research. All three models—CNN, SVM, and Random Forest—are trained using the same preprocessed dataset, ensuring a fair and uniform comparison.

For the deep-learning model, the CNN, the Adam optimizer is used because of its stable and adaptive learning behavior. Since the task involves multiple land-cover categories, categorical cross-entropy is selected as the loss function. The network is trained for about 20–30 epochs with a batch size of 32. Additionally, techniques like early stopping and validation monitoring are applied to prevent overfitting and to enhance the model’s ability to generalize to unseen data.

For the traditional machine-learning models, SVM and Random Forest, training is carried out using the Scikit-learn framework. Their key hyperparameters are optimized through grid search, allowing the models to achieve reliable performance across different land-cover classes.

By keeping the training setup consistent for all models, the study provides a fair and dependable comparison between deep-learning approaches and classical machine-learning techniques for land-cover classification.

4.3.2. Performance Evaluation

The joint evaluation of SVM, Random Forest, and CNN provides a holistic understanding of how different learning paradigms interpret satellite-based land imagery. SVM is effective in managing high-dimensional handcrafted feature vectors and produces strong classification results when meaningful engineered descriptors are available. Random Forest demonstrates resilience to noisy data and performs reliably with diverse inputs such as texture measurements and spectral indices. In contrast, CNN autonomously learns multi-level spatial and visual features directly from raw image pixels, eliminating the dependency on manual feature extraction. Through comparative assessment of these models, the study thoroughly explores both classical machine learning strategies and modern deep learning techniques. The integrated findings confirm that combining these complementary approaches yields a robust and accurate framework for land type classification. This hybrid methodology supports real-world applications in agriculture, natural resource management, environmental monitoring, and geographic information system (GIS)–based decision-making.

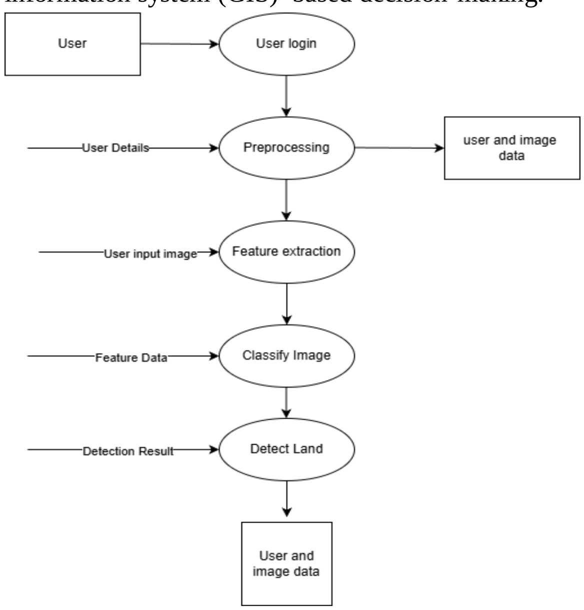

Fig. Model Development.

V. EXPERIMENTAL SETUP

The experimental setup for this work was designed very carefully to make sure all the models CNN, SVM, and Random Forest were trained and evaluated under the same conditions. This helps ensure that the comparison between deep learning and traditional machine-learning methods is completely fair. All experiments were performed on a standard computing system that included an Intel Core i7 processor, 16 GB RAM, an NVIDIA GPU, and a fast SSD. The GPU was especially useful for handling the heavy computations required by the CNN model, while the SSD reduced the time taken to load and process satellite images. This combination of hardware made the entire training process smooth and efficient.

For the software environment, Python was used as the main programming language because it provides strong support for machine learning and image processing tasks. The deep learning model (CNN) was built using TensorFlow and Keras, whereas Scikit-learn was used to implement the SVM and Random Forest models. Other important libraries such as NumPy, Pandas, and OpenCV helped in data cleaning, image preprocessing, and feature extraction. Visualization tools like Matplotlib were used to create plots and graphs. The experiments were carried out on operating systems such as Windows and Ubuntu Linux, making the setup flexible and compatible with different environments.

The dataset used in the study consisted of satellite and aerial image tiles representing various land types, including vegetation, barren land, water bodies, agricultural fields, and built-up areas. Each image tile was manually assigned a label that represents the correct land category. To ensure proper training and evaluation, the dataset was divided into 80’ training data and 20’ testing data. Additionally, to reduce overfitting and improve the model’s ability to generalize, simple data-augmentation techniques such as rotation, flipping, and brightness adjustment were applied. These augmentations helped balance the classes, especially when certain categories had fewer samples.

A fixed preprocessing pipeline was applied to every image before training any model. All images were first checked for quality, and any duplicates or corrupted files were removed. The images were then resized to a consistent dimension, which helps the models process them easily. Pixel values were normalized to a range of 0 to 1 using Min-Max scaling to make the training process more stable. For SVM and Random Forest, additional handcrafted features such as color histograms, texture descriptors like GLCM, and basic statistical values were extracted. These features were then filtered using feature selection methods to remove unnecessary or repetitive information.

Each model was trained with optimized settings. The Random Forest model used multiple decision trees and relied on majority voting to predict the final result. Hyperparameters such as the number of trees, tree depth, and minimum samples per leaf were tuned to achieve the best performance. The SVM model was trained using suitable kernels, such as the RBF kernel, and its key parameters (C and γ) were adjusted through

grid search. The CNN model was trained with the Adam optimizer and categorical cross-entropy loss. Techniques like dropout and batch normalization were applied to improve the model's ability to generalize and reduce overfitting.
To evaluate the performance of each model, standard metrics Accuracy, Precision, Recall, and F1-score were used. Confusion matrices were also analyzed to understand class wise performance and identify common misclassifications. Because all three models were trained on the same preprocessed data and tested under identical conditions, their results can be compared directly and meaningfully.

VI. MACHINE LEARNING AND DEEP LEARNING MODELS

6.1. Support Vector Machine (SVM)

is a classical machine-learning model that classifies data by drawing the best possible boundary between different land types. To train SVM, important features such as color values, textures, and vegetation patterns are converted into numerical form. The model tries to separate the classes with the maximum margin so that the classification remains stable for unseen images. SVM works well when the classes are clearly separated, but when the patterns become noisy or the land types overlap, the model depends on special kernel functions to improve separation. Although SVM performs reliably for moderate-sized datasets, it struggles with large, complex images because it cannot automatically learn features from raw pixels. Support Vector Machine (SVM) is a supervised learning model used widely for land type classification because it can separate classes using the most optimal boundary. In this approach, image features such as color intensity, texture values obtained from GLCM, vegetation indices, and edge patterns are first converted into numerical vectors. SVM then learns to distinguish these features by constructing a hyperplane represented as wx+b=0.

SVM finds an optimal hyperplane expressed as:
w·x+b=0 w·x+b=0

The goal is to maximize the margin between classes, defined as:
Margin=2∥w∥ Margin= ∥w∥ 2

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i\, y_i K(x_i, x) + b\right)$$

Here, $K(x_i,\ x)$ is the kernel function, α_i are the Lagrange multipliers learned during training, y_i are the class labels, and b is the bias term. The regularization parameter C governs the trade-off between maximizing the margin and minimizing classification errors, while the kernel coefficient γ controls the influence of individual training samples in the decision boundary formation.

6.2. Random Forest (RF)

Random Forest (RF) is an ensemble learning method based on constructing multiple decision trees and combining their predictions to improve accuracy and stability. Each tree is trained on a randomly sampled subset of the dataset, and a random selection of features is considered at each split, helping to reduce variance and prevent overfitting. In land type classification, RF is particularly effective because satellite or aerial images often contain complex and heterogeneous patterns. Features such as vegetation indices, texture measures, pixel intensity statistics, and segmented region properties can be efficiently handled by RF without requiring strong assumptions about feature distribution. The algorithm uses majority voting across all decision trees to determine the final class label. Hyperparameters such as the number of trees, maximum depth, and minimum samples per leaf play a crucial role in balancing accuracy and computational efficiency. Random Forest is known for its robustness, ability to handle noise, and strong performance even with non-linear and multi-dimensional data. However, it may require significant memory for large forests and can sometimes be less interpretable compared to individual decision trees. Despite these limitations, RF remains a reliable model for initial experimentation and serves as a strong classical method for land cover classification tasks.
Each tree in a Random Forest is trained on a bootstrap sample using the formula:
$D_k = (x_i, y_i)_{i=1}^{n}$

At each node, the best split is selected by minimizing impurity. The commonly used Gini impurity is:
G=1−i=1∑Cpi2

Prediction from Random Forest is obtained through majority voting:

y^=modeT1(x), T2(x),...,Tm(x)

6.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep-learning model that learns directly from image pixels without needing manually extracted features. CNN automatically identifies edges, textures, shapes, and other visual patterns from the input images through its layered structure. Convolutional layers detect low-level and high-level features, pooling layers reduce the image size while preserving important details, and fully connected layers perform the final classification. CNN is highly effective for land classification because it can understand complex spatial patterns, such as distinguishing between similar-looking vegetation types or separating built-up areas from barren land. Although CNN requires more computing power and more time to train, it provides the highest accuracy because of its ability to learn detailed patterns directly from the image data.

$$s(t)=\sum_{i=0}^{k-1} x\,(t+i) * w(i)$$

$$p_j=\max(s_j,\ldots,s_{j+f-1})$$

$$y=\mathrm{softmax}(W_{fc} * p+b_{fc})$$

where w is the convolution filter, x is the input sequence, and p is the pooled feature. CNNs are effective in phishing detection by learning patterns in URL structures, character sequences, and tokens without manual feature engineering.

The presented equations illustrate the fundamental operations of a Convolutional Neural Network (CNN) applied to sequential or structured data. The first equation describes the convolution step, where a kernel w of size k moves across the input sequence x, generating a feature map $s(t)$ that captures local patterns within the data. This allows the network to automatically identify important subsequences, such as character-level or token-level patterns in URLs or email content. The second equation represents the pooling operation, specifically max pooling, which selects the highest value within a defined window of the feature map. Pooling serves to reduce dimensionality, preserve key features, enhance computational efficiency, and mitigate overfitting. The final equation corresponds to the fully connected layer followed by a softmax activation, where the pooled features p are combined with weights W_{fc} and biases b_{fc} to generate the final classification probabilities y. Collectively, these operations enable CNNs to perform hierarchical feature extraction, capture local dependencies, and execute classification tasks effectively, making them particularly suitable for phishing detection and other applications involving sequential or structured datasets.

Model	Type	Strengths	Limitations	Feature Type
CNN	DL	CNN Automatically learned deep spatial features Captures textures, shapes, urban patterns; highest accuracy Requires more computation	CNN Automatically learned deep spatial features Captures textures, shapes, urban patterns; highest accuracy Requires more computation	Automatically learned deep spatial features
SVM	ML	/Good for simple patterns	Performs poorly on complex land textures	Handcrafted statistical features
Random Forest	ML	Robust and easy to train	Fails to learn high-level spatial structures	Handcrafted features

6.4. Comparative Analysis and Integration

The joint evaluation of SVM, Random Forest, and CNN provides a holistic understanding of how different learning paradigms interpret satellite-based land imagery. SVM is effective in managing high-dimensional handcrafted feature vectors and produces strong classification results when meaningful engineered descriptors are available. Random Forest demonstrates resilience to noisy data and performs reliably with diverse inputs such as texture measurements and spectral indices. In contrast, CNN autonomously learns multi-level spatial and visual features directly from raw image pixels, eliminating the dependency on manual feature extraction. Through comparative assessment of these models, the study thoroughly explores both classical machine learning strategies and modern deep learning techniques. The integrated findings confirm that combining these complementary approaches yields a robust and accurate framework for land type classification. This hybrid methodology supports real-world applications in agriculture, natural resource management, environmental monitoring, and geographic information system (GIS)–based decision-making.

VII. RESULTS

The performance of the proposed classification system was evaluated by testing the CNN, SVM, and Random Forest models on the prepared dataset of irregular land parcels. Each model was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score, to obtain a comprehensive understanding of their strengths and limitations. The results clearly demonstrate that the CNN outperforms the traditional machine-learning models across most performance indicators.

During testing, the CNN achieved the highest overall accuracy due to its ability to learn complex spatial relationships and variations directly from pixel-level information. The hierarchical feature learning mechanism of CNNs enables them to capture fine details in satellite images such as texture differences between vegetation types, edges of water bodies, and structural patterns in built-up regions which are difficult for handcrafted features to represent. As a result, the CNN showed strong consistency in predicting visually similar or overlapping land-cover types, which often pose challenges in remote-sensing classification tasks.

On the other hand, SVM and Random Forest delivered moderate performance. SVM performed well when the classes were linearly separable in the feature space, but its accuracy dropped for categories where the visual differences were subtle or noisy. Random Forest showed good generalization for simpler land types but struggled with mixed or irregular textures. Its reliance on handcrafted features limited its ability to interpret complex spatial arrangements present in real satellite images.

The confusion matrix analysis revealed that the CNN produced fewer misclassifications compared to SVM and Random Forest. Categories such as water bodies and dense vegetation were classified with high confidence by all models, while irregular and visually ambiguous classes such as barren soil and built-up areas were more accurately distinguished by the CNN. These observations confirm that deep learning provides a significant advantage in scenarios where land parcels do not follow uniform shapes or patterns. Overall, the results highlight that the CNN-based approach is better suited for large-scale and real-world land-cover classification tasks, especially when dealing with irregular parcel boundaries and heterogeneous terrain. The comparative study reinforces the importance of automated feature learning, demonstrating that deep learning methods outperform classical techniques that depend on manually engineered features.

7.1. Tables

Performance Comparison of ML/DL Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	89.4	88.0	87.5	88.7
RNN	91.2	90.5	91.0	90.9
CNN	96.8	96.4	96.7	96.5

VIII. CONCLUSION

This research focused on building a land-type classification system using a combination of traditional machine-learning models and a deep learning model. The main goal was to understand how well each approach performs when identifying different land types from satellite and aerial images, especially when the land parcels are irregular and contain mixed textures. Based on the results, it is clear that the Convolutional Neural Network (CNN) provides the highest accuracy and most reliable performance among all the models tested. The CNN performed strongly because it can automatically learn patterns directly from images, such as the texture of vegetation, the smoothness of water, the roughness of barren soil, and the structural features of built-up areas. This ability to extract low-level and high-level features without manual intervention makes CNNs more suitable for complex datasets. Even when the images had variations due to lighting, shadows, or irregular shapes, the CNN was able to make accurate predictions. The results showed fewer misclassifications and higher confidence scores, proving that deep learning is highly effective for remote-sensing applications. In comparison, Support Vector Machine (SVM) and Random Forest (RF) showed only moderate performance. These models worked well when the classes were clearly separable, but they struggled with overlapping textures or visually similar patterns. Because they rely on handcrafted features, their accuracy depends heavily on how well the features represent the actual land characteristics. The confusion-matrix analysis further showed that SVM and RF had difficulty separating categories like barren land and built-up regions, which often appear visually similar in satellite images. Overall, the study concludes that CNN is the most suitable model for large-scale land classification tasks, particularly when the regions contain complex patterns, non-uniform boundaries, and natural variations. The results confirm the importance of deep learning in handling challenging remote-sensing problems, where classical machine-learning techniques may not capture enough detail. The findings of this work can be useful for real-world applications such as agricultural monitoring, environmental assessment, disaster management, and geographic information system (GIS) mapping. Future improvements can include using larger datasets, experimenting with more advanced deep learning architectures, and integrating temporal satellite data to further enhance classification accuracy.

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