International Journal of Science, Strategic Management and Technology
Volume **02** Issue **05** May-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

An Explainable Deep Learning Framework for Land use and Land Cover Classification using Remote Sensing

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https://doi.org/10.55041/ijsmt.v2i5.212

Cite this Article: B.Muthukkumaran, (2026). An Explainable Deep Learning Framework for Land use and Land Cover Classification using Remote Sensing. International Journal of Science, Strategic Management and Technology, *02*(05). https://doi.org/10.55041/ijsmt.v2i5.212

Abstract

Land use classification is an important job in remote sensing. It helps in many areas like planning for city growth, protecting the environment, managing disasters, and using resources wisely. This study presents a complete deep learning system designed to predict land use accurately and in a way that is easy to understand using images from satellites and drones. The process starts by improving the images using techniques like histogram equalization and Gaussian smoothing. These methods help make the contrast better and reduce noise, which in turn makes the important details easier to see. Next, the picture segmentation stage is used to separate important areas in image. This helps the model concentrate on important features likes groups of plants, bodies of water and constructed areas. The images are then send to a simple Convolutional neural network (CNN), which is a popular type of deep learning system. This network is built to quickly sort different land use types, such as urban areas, forests, water, agriculture and roads. The model is designed to work well and use computer resources efficiently, which makes it great for real time and large scale uses. To improve how clear the model is the framework uses Gradient weighted Class activation mapping. This technique creates visual heat maps that show which parts of an image have the biggest impact on the classification decision. The system also provides probability scores for each class, which helps users understand how confident the predictions and how uncertain they might be. Tests show that the suggested method achieves high accuracy in classifying data while also being easy to understand. This tackles a major drawback of traditional black box models. This system is very useful for analyzing geographic information, making policies, and creating smart monitoring systems.

Keywords: Remote sensing, Convolutional Neural Network, Deep learning, Grad-CAM, Environment land use.

Keywords— List 4–6 relevant keywords separated by semicolons.

I. INTRODUCTION

Classifying land use and land cover (LULC) is an important job in remote sensing and geospatial analysis. This classification helps in various areas, including city planning, farming oversight, environmental protection, and disaster evaluation. Correctly identifying different types of land like cities, forests, lakes, farms, and roads, is important for making smart choices in government and

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businesses. As high quality satellite and aerial images become more available, deep learning methods, especially convolutional neural networks(CNN),have performed exceptionally well in classifying images. CNNs can automatically pick up important details from images, doing better than old school machine learning methods that depend a lot on features made by hand. Even though deep learning models are very accurate, they can be hard to understand. This makes it tough for users to see why the models make certain predictions. To solve these problems, this study suggests for users to see why the models make certain predictions. To solve these problems, this study suggests a complete and easy to understand deep learning system for classifying land use. The pipeline uses image enhancement methods like histogram equalization and Gaussian blur to make important features more visible. After that, it segments the image to concentrate on the key areas. A simple CNN is used for classification, and Grad-CAM visualizations help explain the results by showing the areas that have the biggest impact on the predicted class. The class probability distributions, which show how sure the model is about its predictions. This helps makes better and more trustworthy decisions. This propose method brings together the benefits of preparing images, deep learning, and clear explanations. It creates an effective way to accurately and transparently classify land use using satellite images.

II. LITERATURE REVIEW

In recent development in Land Use us and Land Cover (LULC) classification have been significantly driven by deep learning techniques. **Shengyu Zhao et al.2023** presented a comprehensive review od DL based LULC classification, covering models such as CNNs,RNNs,GANs,and Transformers. The study highlights improved accuracy adue to automatic feature extraction while identifying challenges like data imbalance and limited labeled samples. Similarly, **Reem alali 2022** compared traditional Machine Learning techniques such as SVM, Random Forest and K-NN with deep learning approaches. The study emphasizes that ML methods rely on handcrafted features, Whereas DL models automatically learn spatial representations, leading to superior performance, especially in large scale datasets. The importance of temporal data is highlighted by Manuel Campos **Taberner et al.2019** who utilized sentinal-2 time series data for improved classification. Their work also addresses interpret ability challenges, emphasizing the need for Explainable AI techniques to overcome the black box nature of deep learning models. A broader perspective on AI advancements in remote sensing is provided by **Firas F.et al 2021** discussed the transition from traditional image processing methods to DL based models. Their study highlights improvements in accuracy, automation, and the ability to process high resolution and multi spectral data. In comparative studies on segmentation models by **Mengmeng Hao et al 2020** demonstrate that models like swin U net provide enhanced accuracy and robustness. Similarly, advanced segmentation using DeepLabV3+ with Exception backbones (2021) shows improved boundary detection and performance in complex environments. The effectiveness of transfer learning is demonstrated by K. Naushad et al.2020 showed the fine tuning pre trained CNN model significantly improves classification accuracy while reducing training time, particularly in scenarios with limited labeled data. A hierarchical classification approach is proposed by **Chun Yang et al 2018** where land use classes are structured into multi-full levels. This method improves classification consistency and reduces confusion between similar classes by incorporating contextual relationships. Transformer based approaches are further explored by **Teymoor seydi et al.2022** introduced multi model frameworks integrating optical and SAR data. Their work demonstrates that hybrid CNN-transformer models effectively capture both local and global features, improving robustness under challenging conditions. Advancements in transformer models are also presented by **Kai Wang et al 2023** through the LC4-DviT framework. This model incorporates deformable attention and generative augmentation, leading to improved performance and better handling of complex land cover patterns. Interpret ability in deep learning is addressed by **Zhan He et al.2019** combined capsule networks with Grad-CAM to enhance both accuracy and explainability. Additionally,Ioannis Kakogeorgiou and Konstantinos Karantzalos 2021 evaluated various XAI techniques for multi model classification emphasizing the importance of transparency and reliability. The evolution of deep learning in urban land use classification is reviewed by **Zhang et al 2021** highlighting the shift from traditional ML methods to advanced DL and hybrid architectures. The study also emphasizes the importance of contextual and hierarchical information. The effectiveness of CNNs in remote sensing is demonstrated by **Pelletier et al 2019** showing that CNNs outperform traditional classifiers by automatically extracting hierarchical features from raw imagery. P reprocessing techniques are explored by **Mauro Paresis and Jon Atli**

Benediktsson 2001 introduced Morphological attribute profiles(MAPs) for feature extraction improving spatial representation in classification tasks.The importance of large scale datasets is highlighted by **Michael Schmitt et al 2019** through the SEN12MS dataset, which integrates SAR and optical data multi model learning. Benchmarking of CNN architectures is conducted by Xu et al demonstrating that advanced architectures like Res Net and Dense Net outperform traditional CNN models. Spatio temporal analysis using deep learning is explored by Ji et al.2018 Where 3D CNNs are used to capture both spatial and temporal feature for dynamic land use mapping. Data augmentation using GANs,introduced by Ian **Goodfello et al 2014** has been widely applied in remote sensing to address data scarcity and improve model generalization. Finally, semantic segmentation using U-Net, proposed by Jonathan Long et al. 2015 remains a foundational approach due to its encoder decoder structure and ability to preserve spatial details, although it requires enhancements for capturing global context. The above literature review shows a clear transition from traditional ML techniques to advanced DL and transformer based models. While significant improvements have been achieved in accuracy and automation, challenges such as high computational cost, data dependency, and lack of interpret ability still persist, motivating the need for hybrid architectures like CNN-VIT with CBAM.

III. METHODOLOGY

Existing Work

Over the last ten years, the classification of land use and land cover through satellite and aerial images has been thoroughly researched, with conventional methods depending on features created by hand like texture, shape, and spectral indices. Traditional machine learning approaches such as support vector machines (SVM),random forest, and k-nearest neighbors have been used for land cover classification. The effectiveness is frequently restricted by feature selection and their failure to identify hierarchical spatial patterns in high resolution images. Progress in deep learning especially through convolutional neural networks (CNNs) has automatically derive hierarchical features removing the requirement for hand crafted descriptors. Models like U-Net, Segnet and different variations of ResNet are commonly employed for classifying and semantically segmenting remote sensing images. Hao et al in 2022 showed that high resolution satellite images, when used with CNNs,can effectively differentiate urban, forest and agricultural regions. Methods such as Grad-CAM and attention mechanisms enable users to see the areas that greatly influence the models predictions improving transferability and reliability. The creation of a comprehensive pipeline that integrates image enhancement, segmentation, deep learning classification, and interpretable results as suggested in this research. The subsequent research gap identified includes insufficient preprocessing for feature enhancement, lack of integrated segmentation, low interpretability of predictions, limited end-to-end pipeline, and restricted multi class probability insights. The existing gaps highlight the necessity for a cohesive, transparent, and improved land use and confidence metrics, connecting deep learning studies with practical geo spatial applications.

Proposed work

The existing method address the limitation in existing studies this research proposes an end-to-end explainable deep learning pipeline for land use classification from satellite and Ariel imagery. The proposed work aims to develop a comprehensive, transparent and high accuracy framework that combines image enhancement, segmentation, classification and explainable AI in a single process.
This integrated approach is expected to outperform convolutional methods in both accuracy and interpretability, making it suitable for real world land use and land cover analysis. Image Enhancement: The preprocessing techniques such as histogram equalization and Gaussian smoothing to improve the visibility of subtle features in heterogeneous land use regions. This step aims to provide a cleaner and more informative input to the deep learning model. Histogram techniques problematically represented as global contrast by redistributing pixel intensity values so that they span the full

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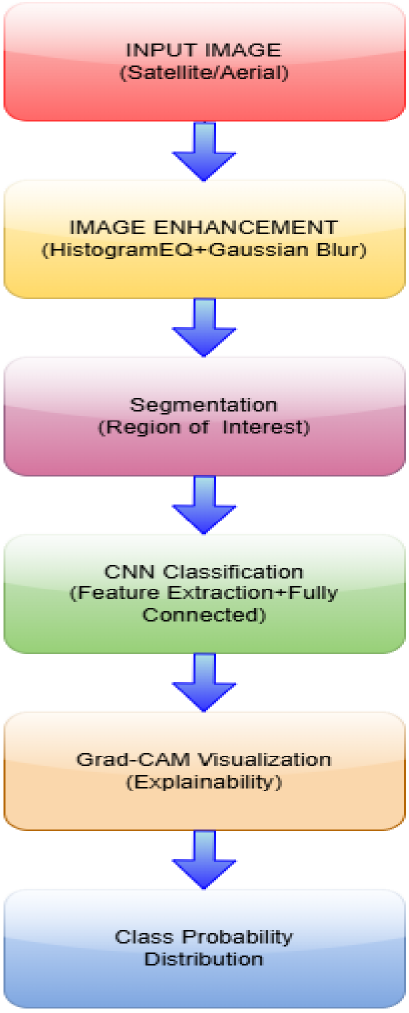

Fig 1: Workflow of the proposed Land use Classification system using CNN and Grad-CAM

dynamic range [0,L-1].The histogram equalization is improves contrast by spreading out intensity values making the hidden features more visible. In histogram calculation is h(i)=Number of pixels with intensity i. The cumulative distribution function (CDF) CDF(i)= $\sum_{j=0}^{i} h(i)$ The overall transformation is T(i)= $\frac{L-1}{M \times N} \cdot \sum_{j=0}^{i} h(i)$. where:L-No of intensity levels, $M \times N$ -Total no of pixels(i)-histogram frequency(i)-mapping function that redistributions intensity. The low contrast represented as pixel values clustered .In histogram equalization spreads item across full range and result is better visibility (road, veitation, water).Segmentation: The Gaussian smoothing is used to removing noise and small variations while preserving overall structure. Gaussian kernel represented as G(x,y)=$\frac{1}{2\pi\sigma 2}$ exp $(\frac{x2+y2}{2\sigma 2})$ Gaussian kernel symmetric and smooth they are controlled by small σ-Slight flur and large σ –heavy flur convolutional smooth operation is

$$Ismooth(x,y) = \sum_{m=k}^{k} Ihc(x-m, y-n)G(m,n), where * convolutional\ output, G(m,n) = Gaussian\ weight\ at\ offset(m,n), k - kernal\ size$$

Each pixel becomes a weighted average its neighbors, nearby pixels contribute more (center has highest weight), noise is reduced edges slightly softened. Then the combined enhancement process is I(x,y,c) -> I_{hc} -> Ismooth(x,y).Smoothing technique General function S(x,y)=f(Ismooth(x,y)),Where S(x,y):segmentation mask.f(.):mapping function that assigns each pixel to a class(foreground/background or multiple region).The threshold segmentation

$$S(x,y) = \begin{cases} 1, & Ismooth(x,y) > r \\ 0, & otherwise \end{cases}$$

Where T-Threshold values(x,y)=1 pixel belongs to region of interest.(ROI),S(x,y)=0 pixel belongs to background. The threshold with a if pixel intensity is high represented as important region, and low represented as ignored. Region of interest is

$$Iroi(x,y) = \begin{cases} Ismooth\ (x,y), & S(x,y) = 1 \\ 0, & S(x,y) = 0 \end{cases}$$

.Rate of Interest retains land areas, background is suppressed. The segmentation used as removes irrelevant background, reduces computational complexity, improve CNN focus on meaningful patterns, and enhances classification accuracy.Then employ a light weight convolutional Neural Network (CNN) to classify images into multiple land use categories, such as Urban, Forest, Water, Agriculture and road. The CNN is trained to automatically extract hierarchical spatial and spectral features, improving accuracy over traditional handcrafted approaches. Mathematically represented as

$$\hat{y} = \arg max\ (Softmax(Wf.(\sigma(Wl * (..\sigma(W2 * \sigma(W1 * X + b1) + b2..+bl)) + bf))).$$

In integrate Grad-CAM visualization to highlight the regions that most influence the model's predictions. This enhances interpretability and provides insights into the decision making process of the deep learning model has been mathematically represented as Grad-CAM formula $L^{c}_{Grad\text{-}CAM}$=ReLU$(\sum_k \alpha Ak)$,and weighted calculation is $\alpha k = \alpha \frac{1}{Z} \sum \sum \frac{\partial yc}{\partial Ak}$,where Ak=feature map from the last convolutional layer, yc=score for class c(eg. forest, urban), αck = importance weight of feature map k, ReLU=keeps only positive influence regions. Then class probability distribution analysis provide a confidence measures for pre dictions and enabling more informed decision making in applications such as urban planning, environmental monitoring and disaster management. For Class probability Distribution analysis, the mathematical representation is typically based on the Softmax function,

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which converts model outputs (logits) into probabilities. Here is the standard formula is

$P(y = i|x) = \frac{e^{zi}}{\sum_{j=i}^{k} e^{zj}}$,Where, P(y=i|x)-Probability of class I given input x. zi- logit (raw output)for class i, k-Total number of classes, e-Exponential function and for decision making Final prediction is represented as ŷ=arg max P(y=i|x) then confidence level formula represented as Confidence=max P(y=i|x).This formulation is essential in applications like urban planning(land classification confidence),Environmental monitoring(uncertainty aware predictions) and disaster management(risk based decision support).

IV. RESULTS AND DISCUSSION

In this paper use the Euro Sat dataset for classification in Annual crop, forest, highway, industrial etc.,.The experimental assessment of the suggested CNN-driven land use classification system a shows moderate effectiveness on the multi class dataset ,attaining an overall accuracy of 41%,accompanied by a macro average F1-Score of 0.31 and a weighted F1-score of 0.33.The findings suggest that the model can learn distinguishing features for specific land types like forest, industrial and river, showing noticeably higher recall and F1-score.Specifically,the forest class achieves a recall of 0.91,showcasing the model's capacity to accurately identify dense vegetation patterns, whereas industrial regions attain a recall of 1.00 because of their unique structural features. Nonetheless, the model shows considerable shortcomings in recognizing categories like Herbaceous Vegetation, Highway, and sea/lake, with both precision and recall values at zero, signifying total misclassification. This implies a lack of adequate feature representation or on imbalance among classes in the training data. Moreover, the confidence in the predictions stays quite low, as shown by the output where the predicted class river reaches merely 29.89% probability, with other classes like pasters having closely competing probabilities. This indicates uncertainty in acquired characteristics and overlapping spatial configurations among specific land types. In summary, although the suggested method shows the practically of combining preprocessing, CNN based classification, and explain ability, the findings emphasize the necessity for better model generalization, stronger feature extraction, and balanced training data to obtain more dependable and resilient land use classification. In this paper used the random images Fig1 and Fig 2 shows the land use classification and probability.

Fig-1:Original Image

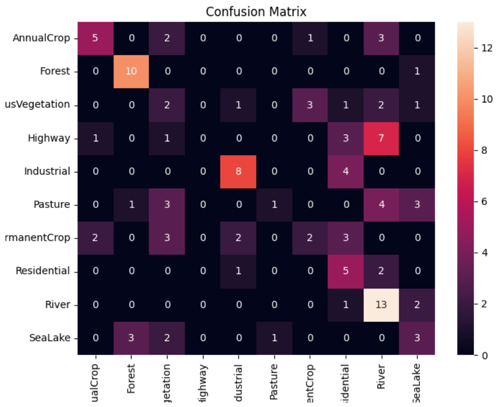

Fig-1a:Confusion Matrix

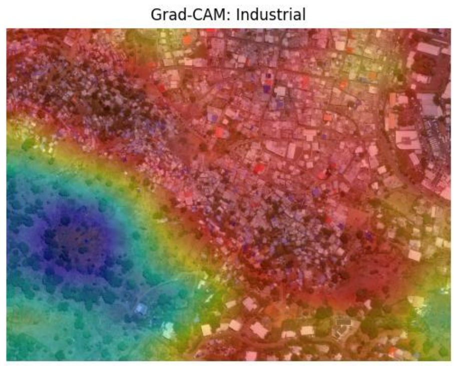

Fig-1b:Grad CAM View

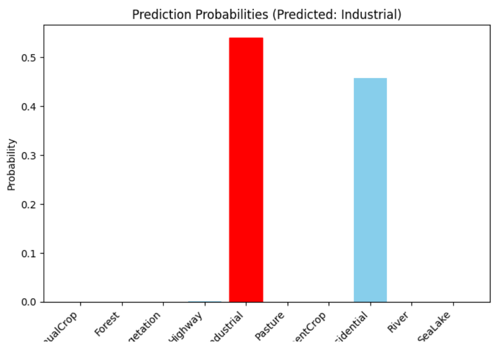

Fig-1c:Prediction Probability

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Fig-2.Original Image

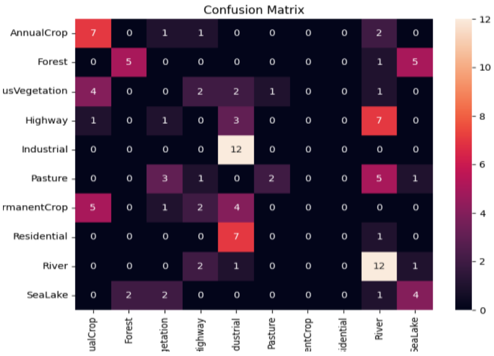

Fig-2a:Confusion Matrix

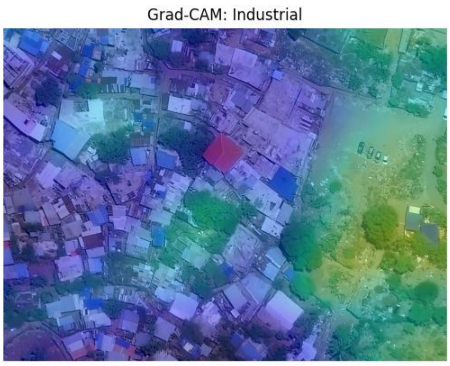

Fig-2b:Grade CAM View

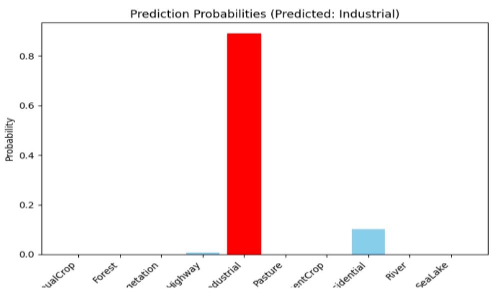

Fig-2c:Prediction Probability

Class	Precision	Recall	F1-Score
AnnualCrop	0.62	0.45	0.53
Forest	0.71	0.91	0.8
HerbaceousVegetation	0.15	0.2	0.17
Highway	0	0	0
Industrial	0.67	0.67	0.67
Pasture	0.5	0.08	0.14
PermanentCrop	0.33	0.17	0.22
Residential	0.29	0.62	0.4
River	0.42	0.81	0.55
SeaLake	0.3	0.33	0.32

Table-1 Precision, Recall and F1-score

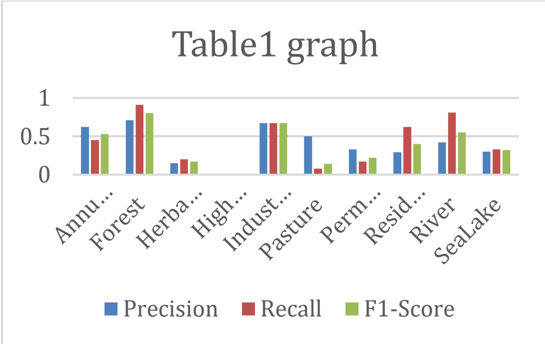

Fig 3- Precision, Recall and F1-score Graph representation

Class	Probability
AnnualCrop	0
Forest	0
HerbaceousVegetation	0
Highway	0.002
Industrial	0.5396
Pasture	0
PermanentCrop	0.0001
Residential	0.4583
River	0
SeaLake	0

Table-2 –Probability of fig 1

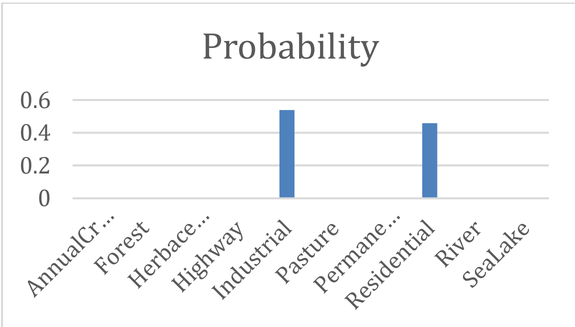

Fig 4-Probability graph

Summary	Value
Predicted Class	Industrial
Sum of Probabilities	1

Table-3 Probability Summary

Then calculate another figure Fig-2 probability , precision f1 score, and recall shows

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Class	Precision	Recall	F1-Score
AnnualCrop	0.41	0.64	0.5
Forest	0.71	0.45	0.56
HerbaceousVegetation	0	0	0
Highway	0	0	0
Industrial	0.41	1	0.59
Pasture	0.67	0.17	0.27
PermanentCrop	0	0	0
Residential	0	0	0
River	0.4	0.75	0.52
SeaLake	0.36	0.44	0.4

Table -4 Precision, Recall and F1-score

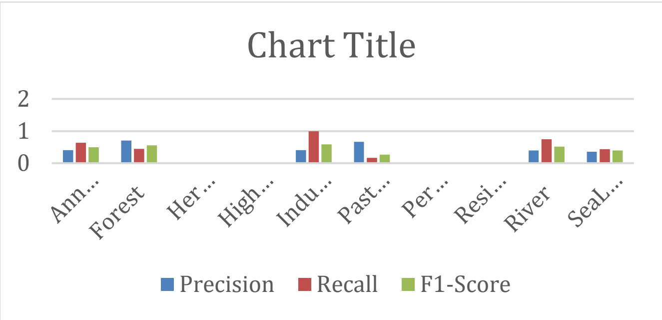

Fig 5- Precision, Recall and F1-score Graph representation

Class	Probability
AnnualCrop	0.0001
Forest	0
HerbaceousVegetation	0.0002
Highway	0.0065
Industrial	0.8896
Pasture	0
PermanentCrop	0.0005
Residential	0.1028
River	0.0003
SeaLake	0

Table 5- Probability of fig 2

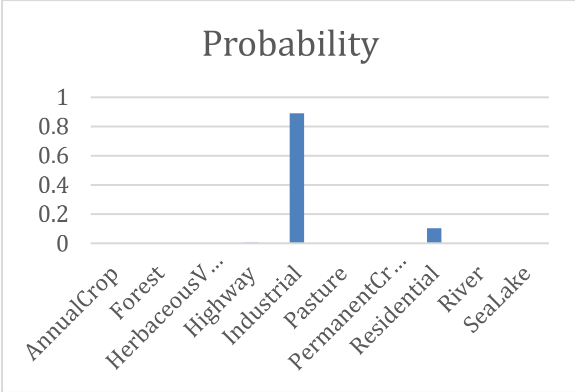

Fig 6- Fig 4-Probability graph

Summary	Value
Predicted Class	Industrial, Residential
Sum of Probabilities	1

Table-6 Probability Summary

The proposed deep learning based land use and land cover classification framework was evaluated using multiple land categories. The system performance was analyzed using Precision, Grad-CAM visualizations, and probability distribution graphs. In Fig-1, the original satellite image underwent processing via the trained CNN model. The confusion matrix shown in fig-1a illustrates the network's classification performance across all land use categories. The Grad CAM visualization depicted in fig-1b emphasizes the significant areas of the image that the model utilizes for its predictions. The probability distribution graph in Fig-1c shows that the model classified the image primarily as industrial with a probability of 0.5396,wheras Residential received the next highest probability of 0.4583.According to Table-1,the model exhibited impressive results for the forest class, attaining a Precision of 0.71, a recall of 0.91,and an F1-Score of 0.80,demonstrating that forest areas were correctly identified. The Industrial class demonstrated consistent performance with all metrics matching at 0.67, Nevertheless categories like Highway, Pasture, and Herbaceous Vegetation yielded lower scores because of the similarities in texture and spatial patterns within these groups. The probability, summary presented in Table-3 verifies that the total probability values add up to 1, confirming the proper functioning of softmax classification. As the Industrial class received the top confidence score, the model categorized Fig-1 as an Industrial land use area. For Fig-2, the CNN model processed the input image once more, producing the associated confusion matrix, Grad-CAMM visualization, and probability graph. The Grade-CAM activation map shown in Fig-2b distinctly highlights the key areas evaluated by the network while classifying.Table-4 shows that the Industrial category attained the highest Recall value of 1.0, indicating that every Industrial sample was accurately identified. The Annual Crop class demonstrated moderate performance with Precision 0.41, Recall 0.64 and F1-score 0.50.The River class demonstrated a satisfactory classification ability with a Recall of 0.75.Certain categories like Herbaceous Vegetation, Highway, and Permanent Crop received lower scores due to overlapping visual traits and a lack of distinct features. The probability analysis presented in Table-5 indicates that the model assigned a very high confidence score of 0.8896 to Industrial, whereas Residential was given a probability of 0.1028.The other classes received minimal probability values. Consequently, the image in Fig-2 was mainly categorized as Industrial, with minor resemblance to Residential areas. The probability summary in Table-6 confirms the correctness of the prediction distribution, where the cumulative probability equals 1.

V. CONCLUSION

The suggested study introduces an explainable deep learning system for Land Use and Land cover (LULC) classification through remote sensing images by combining image enhancement, segmentation, CNN-based classification, Grade CAM visualization, and Probability based confidence evaluation into a cohesive end to end process. Experimental findings on the EuroSAT dataset showed the model's ability to classify various land types, including Forest, Industrial, River, and Residential and Annual crop, with satisfactory results. The incorporation of Grad-CAM enhanced the system's interpretability by visually pin pointing key areas affecting predictions, while softmax probability assessment offered confidence metrics for trustworthy decision making. The innovation of this research resides in integrating preprocessing, explainable AI, confidence driven prediction assessment and a lightweight CNN structure into one framework, thus closing the divide between classification precision and model clarity. The suggested method provides real world utility in urban development, ecological observation, framing, and crisis response, whereas future enhancements can target sophisticated hybrid frameworks, attention systems and the incorporation of multi temporal satellite information for improved reliability and precision.

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