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RESEARCH ARTICLE

FuzzyVGG: Improving Uncertainty and Interpretability in Satellite Image Classification through Fuzzy Logic Integration

FuzzyVGG: Melhorando a Incerteza e a Interpretabilidade na Classificação de Imagens de Satélite através da Integração de Fuzzy Logic

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Abstract: Convolutional neural networks (CNNs) have demonstrated impressive performance in image recognition tests due to their deep hierarchical feature extraction capabilities. But when it comes to satellite imagery, which frequently has inherent uncertainties like shifting lighting, unclear object boundaries, and overlapping classes, these conventional models provide serious difficulties. Standard CNN architectures may perform less well as a result of these ambiguities. To address these limitations, this study introduces a novel hybrid approach called Fuzzy VGG, which integrates fuzzy logic into the VGG16 and VGG19 architectures. The primary objective is to enhance model interpretability and robustness in handling the uncertainties present in satellite image data. Our method replaces the conventional dense-softmax output layer with a custom fuzzy classification layer that represents soft class membership using cosine similarity. Our experiments on the UC Merced Land Use dataset show that the integration of fuzzy logic leads to significantly improved performance. The Fuzzy VGG16 model achieved an accuracy of 90%, while Fuzzy VGG19 reached 97% accuracy. This represents a consistent performance gain of 15% over the standard VGG16 (75% accuracy) and VGG19 (80% accuracy) models. These results confirm the effectiveness of our hybrid system in creating a more robust and reliable decision-making mechanism for complex image classification tasks. On a medical dataset, the fuzzy VGG model achieved an overall accuracy of 96%, with macro and weighted averages for precision, recall, and F1-score all equal to 96%.
Keywords: deep learning — satellite image classification — fuzzy logic — uncertainty handling — hybrid models — interpretability

Resumo: Redes neurais convolucionais (CNNs) têm demonstrado performance impressionante no reconhecimento de imagens, mas enfrentam dificuldades com imagens de satélite devido a incertezas inerentes, como iluminação variável, limites difusos e classes sobrepostas. Para superar essas limitações, este estudo apresenta o Fuzzy VGG, uma abordagem híbrida que integra lógica fuzzy às arquiteturas VGG16 e VGG19 para aumentar a interpretabilidade e robustez. Nosso método substitui a camada de saída convencional dense-softmax por uma camada de classificação fuzzy personalizada, representando a pertinência de classe difusa via similaridade de cosseno. Experimentos no conjunto UC Merced Land Use demonstram melhorias significativas: o Fuzzy VGG16 alcançou 90% de precisão e o Fuzzy VGG19 atingiu 97%, um ganho consistente de 15% sobre os modelos padrão (75% e 80%, respectivamente). Esses resultados confirmam a eficácia do nosso sistema em tarefas complexas de classificação. Além disso, em um conjunto de dados médicos, o modelo Fuzzy VGG obteve 96% de precisão geral, com médias macro e ponderada para precisão, revocação e F1-score também em 96%.
Palavras-Chave: aprendizado profundo — classificação de imagem de satélite — fuzzy logic — uncertainty handling — hybrid models — interpretability

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1. Introduction

Agriculture, environmental monitoring, natural resource management, and other fields depend heavily on the classification of satellite images [1]. Although the complex and varied character of satellite imagery presents significant challenges, it also provides invaluable insights into the Earth's surface. Accurate categorization is often hindered by variations in lighting, shadows, cloud cover, and indistinct boundaries between land-cover classes. Satellite image interpretation is therefore crucial for extracting meaningful information from large volumes of remote sensing data [2]. Manual analysis is time-consuming, subjective, and unsuitable for large-scale applications, which has led to an increasing demand for automated and reliable classification systems.

Recent advances in DL [3] [4], particularly CNN-based models, have driven major progress in satellite image classification thanks to their strong spatial feature extraction capabilities. CNNs have become the dominant paradigm in image analysis, achieving state-of-the-art performance across many computer vision tasks [5] [6] [7]. In particular, pre-trained CNN architectures have demonstrated remarkable success in visual recognition owing to their deep hierarchical representations [8] [9] [10]. Nevertheless, such models do not explicitly model the uncertainty inherent in remote sensing data, including noise, ambiguous object boundaries, and overlapping classes. Although CNN-based approaches such as VGG16 and VGG19 have shown strong performance, they still struggle to cope with the complexity and ambiguity characteristic of satellite imagery [11] [12].

To overcome these limitations, fuzzy logic provides a principled framework for handling uncertainty by representing gradual class memberships. Recent studies have reported that hybrid strategies combining CNNs with fuzzy-based reasoning can enhance robustness when dealing with noisy or ambiguous data. Building on these developments, this work investigates the integration of fuzzy logic into VGG16 and VGG19 architectures to improve adaptability and interpretability in satellite image classification. Our hybrid approach is evaluated on the UC Merced Land Use dataset, a widely used benchmark in this field [13]. The objective is to demonstrate that incorporating fuzzy inference into pre-trained CNN models leads to improved classification performance through more effective uncertainty management.

The main contributions of our study are:

- We propose FuzzyVGG, a novel hybrid architecture that integrates fuzzy logic into deep CNNs to improve performance, robustness, and interpretability in image classification.
- We replace the standard dense-softmax output layer with a custom fuzzy classification layer that provides a more nuanced and interpretable representation of the model's decisions.
- The model's effectiveness is validated on two distinct benchmark datasets: the UC Merced Land Use dataset for satellite imagery and a medical dataset.

This paper is structured as follows: Section 2 provides essential background on Fuzzy Neural Networks (FNNs), including a brief overview of CNNs and fuzzy logic. Section 3 reviews the literature relevant to this study. Section 4 details the materials and methods, while Section 5 outlines the implementation details. The discussion of our findings is presented in Section 6, and finally, Section 7 offers a conclusion along with potential future directions.

2. Background

This section provides the theoretical foundations necessary for understanding the work presented. It is divided into two subsections. The first focuses on CNNs, a type of neural network particularly well-suited for image processing tasks. The second subsection introduces Fuzzy Logic, an approach used to handle uncertainty and imprecise information. Both concepts play a key role in our methodology and will be combined in the following sections to develop our proposed approach.

2.1 Convolutional Neural Network

CNN is an advanced DL model specifically tailored for processing and analyzing visual data, such as images or videos [14]. Inspired by the principles of the human brain's visual processing, CNNs excel at automatically extracting and learning hierarchical features from input images. The architecture of a CNN is characterized by convolutional layers, which use filters, or kernels, to detect intricate patterns such as edges, textures, and complex structures within images (Figure 1). These layers are often followed by pooling (or subsampling) operations that downsample the spatial dimensions of the feature maps, improving computational efficiency and promoting spatial invariance [15] [16]. Non-linearity is introduced through activation functions such as the Rectified Linear Unit (ReLU), enabling the network to capture complex relationships in the data. The network typically concludes with fully connected layers that integrate the learned features to perform high-level tasks such as image classification or object detection. In classification scenarios [17] [18], a softmax layer is commonly employed at the output to produce a probability distribution over the target classes.

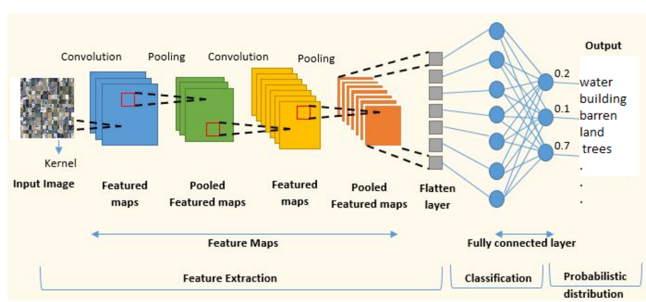

Figure 1. Convolutional Neural Network architecture

Several variants of CNNs have been developed to improve performance and efficiency in specific tasks. Architectures such as LeNet, AlexNet, VGG, ResNet, and Inception have introduced major innovations in image recognition, including deeper network designs in ResNet and more efficient filter arrangements in Inception. Moreover, the widespread use of pre-trained models—initially trained on large-scale datasets such as ImageNet and subsequently fine-tuned for domain-specific tasks—has become a standard practice. This transfer learning strategy significantly reduces training time and enhances accuracy, particularly when labeled data are limited.

Renowned for their prowess in computer vision tasks, CNNs have set benchmarks in fields ranging from image recognition and object tracking to medical imaging and autonomous driving. Their versatility and robustness have made CNNs indispensable in cutting-edge applications where visual data analysis is paramount.

2.2 Fuzzy logic

Fuzzy logic is an approach to reasoning that handles uncertainty and imprecision [19], unlike classical logic, in which statements are either entirely true (1) or false (0). In fuzzy logic, truth values range between 0 and 1, representing degrees of truth, which is particularly useful in situations where distinctions between true and false are not clear-cut. For instance, instead of stating "It is hot" as either true or false, fuzzy logic allows for expressions such as "It is somewhat hot."

A fuzzy system operates through four main stages: fuzzification (transforming real-world data into fuzzy values), rule application through if–then statements, inference (generating fuzzy outputs), and defuzzification (converting fuzzy outputs back into precise values) [20]. A significant advantage of fuzzy logic is its linguistic interpretability [21], which enables human users to better understand complex systems. This is achieved through rule-based representations that explain outputs using intuitive if–then formulations. For example, fuzzy logic can be employed to describe the outputs of complex models such as CNNs by translating their internal mechanisms into a set of comprehensible rules, thereby bridging the gap between automated decision-making and human understanding.

Figure 2 illustrates a typical fuzzy logic process. It includes a fuzzifier that converts crisp inputs into fuzzy membership values, a rule base containing a collection of if–then rules, an inference engine that applies these rules to derive fuzzy outputs, and a defuzzifier that transforms the inferred results into crisp values. The arrows indicate the flow of information between these components from input to output, including a feedback loop to the rule base. This diagram represents a standard fuzzy logic system commonly used in decision-making and classification tasks.

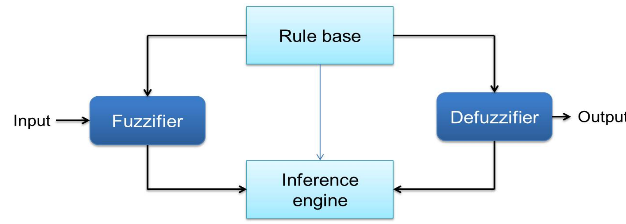

Figure 2. Fuzzy logic architecture

The integration of fuzzy logic with CNNs in satellite image classification represents a significant advancement in remote sensing research. This literature review traces the evolution of methodologies used in high-resolution aerial imagery analysis, with a particular focus on CNN-based approaches for land-cover classification. The foundational work of [22] demonstrated the effectiveness of CNNs in very high-resolution imagery, showing that traditional feature extraction techniques can be enhanced through DL methods. Sherrah emphasized the use of atrous convolution to preserve spatial resolution while generating semantic labels, achieving improved accuracy in detecting infrastructure such as roads and buildings. This contribution highlighted the ability of CNNs to cope with noisy ground-truth labels and established a reference point for subsequent image-classification studies.

Building on this foundation, [23] introduced the Fully Convolutional Network (FCN-8) for RGB satellite image segmentation, addressing land use and land cover (LULC) mapping by projecting learned representations into high-resolution pixel space to enable dense classification. The authors stressed the importance of accurate LULC identification for effective land management, thereby extending CNN applications in environmental monitoring. More recently, [24] presented a comparative study of CNNs and transformer-based models for land-cover classification, reporting high accuracy for both paradigms and confirming the central role of DL in this domain. Rangel et al. further underlined the increasing availability of large-scale remote-sensing datasets and rapid DL advances, indicating promising future directions for land-cover analysis.

Taken together, these studies suggest that augmenting CNN architectures with fuzzy reasoning can further enhance classification performance by explicitly modeling the uncertainty inherent in satellite imagery. Each contribution advances the understanding of how hybrid fuzzy–DL systems can support more reliable environmental analysis and decision-making.

Figure 3 provides an overview of DL architectures that incorporate fuzzy logic. Since 2014, numerous studies have explored this integration to improve uncertainty management, robustness, and performance in complex scenarios. Early efforts included Deep Belief Networks with Fuzzy Granulated Inputs (DBN-FGI) for time-series analysis and Fuzzy Restricted Boltzmann Machines (FRBM), which strengthened uncertainty modeling through fuzzy weighting [25]. Subsequent extensions involved Restricted Boltzmann Machines with Fuzzy Inputs (RBM-FI) [26] and Deep Belief Networks with Fuzzified Outputs (DBN-FO).

Later, approaches such as Intra- and Inter-Fractional Variation Prediction using Fuzzy DL (IFVP-FDL) and DL with Fuzzy Feature Points (DL-FFP) were proposed to enhance image robustness. Takagi–Sugeno Deep Fuzzy Networks (TS-DFN) enabled adaptive fuzzy-rule learning, while Stacked Autoencoders with Fuzzy Logic (SAE-FL) and Fuzzy Autoencoders (FAE) improved parameter adaptation and representation learning. Further developments included Deep CNNs with Weighted Fuzzy Active Shape Models (DCNN-WFASM), Deep Fuzzy Classifier Systems (DFCS), and Type-2 Fuzzy DL Networks (T2-FDLN) for handling higher degrees of uncertainty. Pythagorean Fuzzy Sets embedded in CNNs (PF-CNN) improved performance under ambiguous or incomplete data conditions, and more recently, Fuzzy Variational Autoencoders (F-VAE) have been introduced for self-supervised and unlabeled data classification.

Parallel advances produced ensemble frameworks such as the Hierarchical Fused Fuzzy Deep Neural Network (HF-FDNN) for data classification and Fuzzy Deep Reinforcement Learning (F-DRL), which combines reinforcement learning with fuzzy systems. Collectively, these contributions illustrate the steady evolution of fuzzy-enhanced DL models and demonstrate how fuzzy reasoning strengthens neural architectures for uncertainty management across diverse applications.

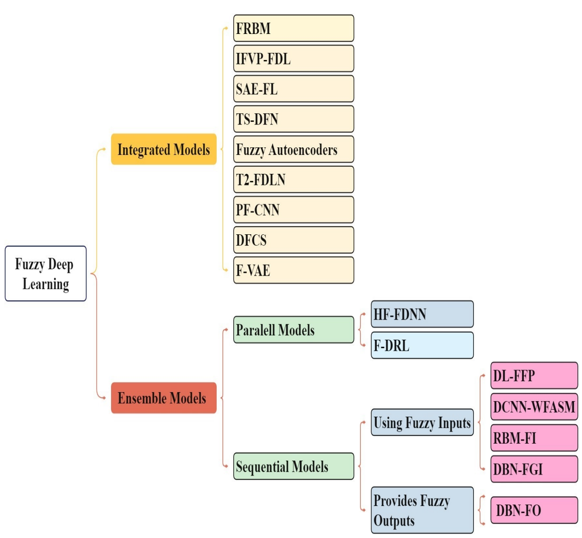

Figure 3. Overview of the different DL models implementing fuzzy logic

3. Literature review

This section provides a review of existing studies in remote sensing, with a specific focus on models that have been applied to the UC Merced Land-Use dataset. These works serve as a critical foundation for evaluating and comparing the performance of our proposed hybrid approach.

The authors, in [27], used CNNs to provide a supervised DL method for classifying satellite images. By correctly classifying earth observation images, the model facilitates real-time processing by analyzing live feeds, including camera or satellite movies, frame by frame. It offers better accuracy and performance across datasets with different class numbers and image sizes since it is scalable. The suggested method exhibits robustness, real-time applicability, and efficient categorization across a variety of satellite image datasets.

A few-shot scene classification system based on metric learning and local descriptors (MLLD) was introduced by the authors in [28] for remote sensing images. By gaining meta-knowledge through task-level meta-learning, the model improves its capacity to identify several categories from sparse samples. While a learnable metric uses local descriptor similarity to match images to their closest category, Manifold Mixup is applied to hidden layers to smooth decision boundaries and simplify feature representations. The suggested approach demonstrated state-of-the-art performance in scene categorization under constrained data settings when tested on the UC Merced, WHU-RS19, and NWPU-RESISC45 datasets.

For multi-source remote sensing images, the authors, in [29], introduced a multi-label classification model that integrates DenseNet with an attention mechanism. For multi-label classification, the sigmoid activation function takes the role of Softmax, and each dense block is supplemented by fusion channel attention and spatial attention modules. By collecting global dependencies, integrating local details, preserving important image features, and combining contextual data, this method improves feature extraction. For remote sensing images, the model showed enhanced multi-label classification accuracy when tested on the SEN12-MS and UC-Merced datasets. achieving a Micro-Precision of 0.90, Micro-Recall of 0.94, Micro-F1 of 0.92, Hamming Loss of 0.033, and overall Accuracy of 0.881.

The authors proposed, in [30], a hybrid model that combines Support Vector Machines (SVM) and deep residual networks. SVMs optimized with a bias-corrected Adam optimizer are used to classify multispectral images after pre-trained residual networks extract discriminative features from the images. The technique manages limited training data and lessens overfitting by substituting SVMs for Softmax and thick layers. When tested on the Eurosat and UC Merced datasets, the suggested DRSVM model demonstrated increased competitive accuracy, reduced time complexity, and efficiency, all of which were further improved with data augmentation.

In order to obtain high accuracy with less processing time, the authors, in [31], suggested a hybrid approach for classifying remote sensing images using the UC Merced Land-Use Dataset. This method uses machine learning techniques like SVM, K Nearest Neighbor, Decision Tree, and Discriminant Analysis to classify the features once they have been retrieved using ResNet18 and GoogLeNet. This combination combines the effectiveness of conventional classifiers with the powerful feature extraction capabilities of CNNs. According to the results, ResNet18 with Decision Tree had the lowest accuracy 50.95%, whereas GoogLeNet with SVM had the greatest 93.33%.

The authors presented MobileTransNeXt, [32], a unique hybrid DL model that combines a CNN and a Transformer. In particular, the model integrates a Transformer into the architecture of MobileNetV2. The two-step procedure at the heart of this suggested approach is that the input image is first converted into a feature map by the MobileNetV2 component, which is then sent into the Transformer for classification. They also presented a deep feature engineering (DFE) method based on MobileTransNeXt, which leverages the model to extract and improve deep features to further increase classification accuracy and show excellent transfer learning capabilities. By combining the advantages of both architectures, this cooperative method produces a novel computer vision solution that uses fewer parameters while yet achieving excellent performance.

By using transfer learning with the Inception-v3 and DenseNet121 CNN architectures, the authors, in [33], developed a land-area classification (LAC) system. Using the UC-Merced Land Use dataset, they refined these pre-trained models to precisely identify different urban land-use groups. By using this method, the models were able to improve their performance and generalizability even with a small amount of labeled data by using knowledge from big, pre-existing datasets. To understand the models' decision-making processes, the researchers employed heatmap analysis. The system obtained 92% accuracy, 93% recall, 92% precision, and a 92% F1-score.

This work's [34] primary contribution is the creation of a transfer learning-based method for remote sensing image classification that makes use of MobileNetV2. The paper shows how an effective model can attain excellent performance while keeping reduced computational complexity by using MobileNetV2's lightweight design and optimizing it using the UC-Merced dataset. With a pre-trained MobileNetV2 and transfer learning, classification accuracy is greatly improved, with impressive results of 91.43% accuracy, 91% kappa index, and 91.50% F1-score. These results demonstrate how well the suggested approach works to identify scenes in remote sensing applications in a robust and trustworthy manner.

More specific models have been presented recently to address the spectral and temporal uncertainty present in raw satellite images, going beyond the well-established hybrid architectures. The study of [35], who created a CNN-Pythagorean Fuzzy Deep Neural Network (PFDNN), is a noteworthy illustration. Their model obtained an accuracy of 96.96% on the EuroSAT dataset by combining the feature extraction capabilities of CNNs with Pythagorean fuzzy set (PFS) theory and using the Optuna framework for automatic hyperparameter optimization. According to their research, adding a Pythagorean fuzzy layer improved performance by about 13.05% when compared to traditional fuzzy systems.

The classification performance of existing related works on the UC Merced dataset is summarized in Table 1, with all results based on the same dataset to ensure a fair comparison.

4. Materials and methods

The proposed model, FuzzyVGG19, introduces a novel hybrid architecture that integrates deep CNN with fuzzy logic principles to improve classification robustness in complex and uncertain visual domains such as Remote sensing images.

Figure 4 shows the adopted methodology used in this study. The methodology comprises a feature extraction phase based on a VGG19 network as a powerful transfer learning model, emphasizing high-level semantic information from input images. In order to reduce computational complexity and to preserve pertinent features, we only adopted four convolutional blocks of the original VGG19 instead of five blocks. After extracting deep features from Block4, FuzzyVGG19 applies global average pooling 2D to reduce dimensionality, followed by fully connected layers and a dropout layer with a dropout rate of 0.5 to prevent overfitting. A final fully connected layer is then attached to the fuzzy layer, responsible for classification. The second phase of FuzzyVGG19 lies in the custom FuzzyClassificationLayer, which replaces the classical dense layer added to the softmax output with a fuzzy-inspired mechanism. Each class in this layer is represented by a learnable center vector within the feature map.

During training, the input features: $\mathbf{x}_i \in \mathbb{R}^d$ and class centers: $\mathbf{c}_j \in \mathbb{R}^d$ be the learnable center representing class j, are normalized with L2 to ensure unit length by applying the followed formula (equation 1):

$$\hat{\mathbf{x}}_i = \frac{\mathbf{x}_i}{\|\mathbf{x}_i\|}, \quad \hat{\mathbf{c}}_j = \frac{\mathbf{c}_j}{\|\mathbf{c}_j\|}. \tag{1}$$

The next step is applying the cosine similarity, which is a fundamental measure of fuzzy membership as described in the following formula (equation 2):

$$\mu_{ij} = \cos(\theta_{ij}) = \hat{\mathbf{x}}_i \cdot \hat{\mathbf{c}}_j = \frac{\mathbf{x}_i \cdot \mathbf{c}_j}{\|\mathbf{x}_i\|\|\mathbf{c}_j\|}. \tag{2}$$

where $\mu_{ij} \in [-1, 1]$ represents the similarity between input i and class j In each fuzzy class, a dot product is applied on the normalized inputs and centers reflecting the degree of appartenance. These scores are then passed through a softmax function to generate an interpretable probability distribution as described in the following formula (equation 3):

$$P(y_i = j \mid \mathbf{x}_i) = \frac{\exp(\mu_{ij})}{\sum_{k=1}^{K} \exp(\mu_{ik})}. \tag{3}$$

where K is the total number of classes.

The decision process was animated by a categorical loss function since it is a multiclassification with 21 classes formulated in equation 4:

$$\mathscr{L} = -\sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \log P(y_i = j \mid \mathbf{x}_i). \tag{4}$$

Table 1. Comparison of classification performance of existing related works on the UC Merced Land-Use dataset

Year	Model	Pre (%)	Sens (%)	Spec (%)	Acc (%)
2025	CNN [27]	–	–	–	89
2023	MLLD [28]	–	–	–	77.76 ± 0.52
2023	DenseNet attention mechanism [29]	90	–	–	88.1
2023	Deep residual SVM [30]	–	–	–	96
2023	GoogLeNet+SVM [31]	–	–	–	93.33
2025	MobileTransNeXt [32]	–	–	–	96.90
2024	Inception-V3 [33]	93	92	–	92
2024	DenseNet121 [33]	91	90	–	91
2024	ResNet-50 [33]	90	90	–	91
2024	MobileNetV2 [34]	–	–	–	91.43

where $y_{ij} \in \{0,1\}$ is the true one-hot encoded label for sample i.

This fuzzy logic-based formulation enables the model to express partial class memberships and handle data ambiguity more effectively than traditional crisp classifiers.

Figure 5. Dataset UC Marced Land

5. Implementation details

5.1 Dataset description

In our work, we propose a customized FNN based on the VGG architecture. This method is applied on the UC Merced Land Use dataset, which consists of 21 categories of high-resolution satellite images, including agriculture, airports, dense residential zones, highways, and more (Figure 5). This dataset presents an interclass visual similarity and ambiguous boundaries, making accurate classification very challenging for conventional models.

5.2 Data preprocessing

The class distribution in the dataset used for this investigation was noticeably unbalanced, with some categories having comparatively few samples and others having overrepresentations. A model may become biased toward majority classes as a result of this discrepancy in data distribution, which would hinder its capacity to generalize across all categories and harm the training process.

A class balancing technique was implemented before training in order to address this problem. In particular, an upsampling technique was used, whereby samples from minority classes were replicated at random until the number of occurrences in each class was equal. By guaranteeing equal representation in every category, this method decreased the

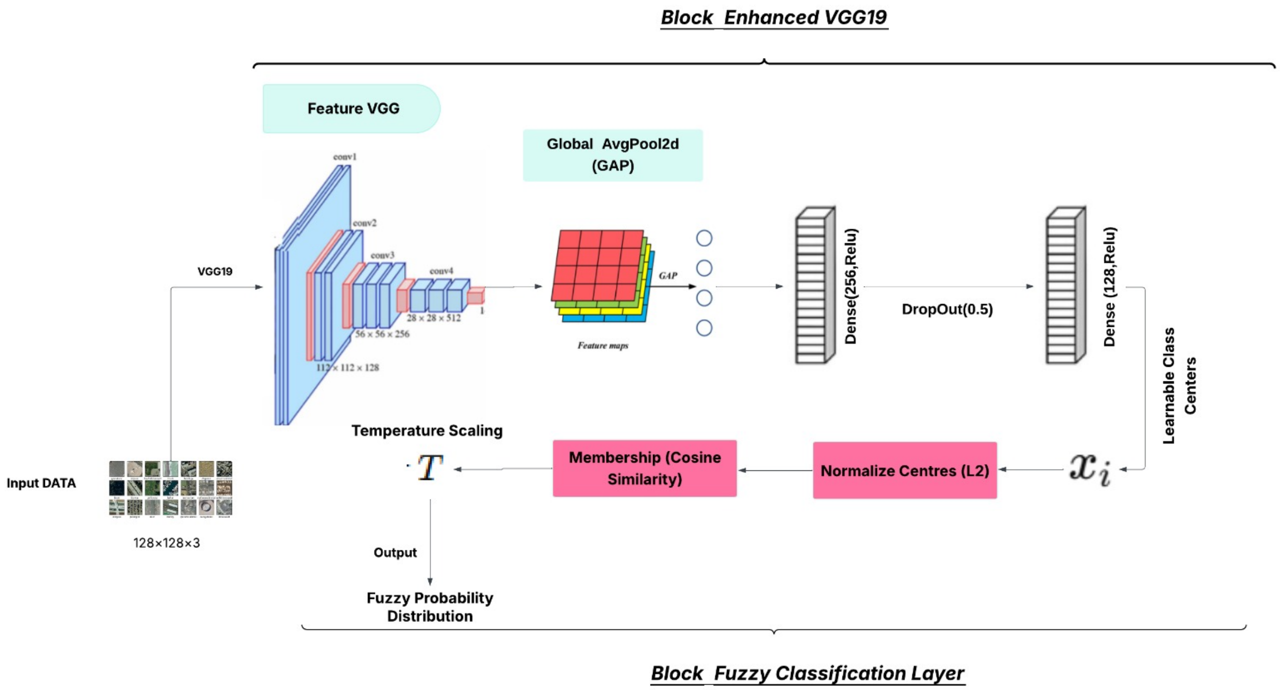

Figure 4. Architecture of the proposed FuzzyVGG model combining VGG19 with a fuzzy classification layer.

possibility of bias and allowed the model to identify more generalized and discriminative feature patterns.

As a result of this preprocessing step, two datasets were prepared for experimentation

- Dataset1: the original dataset with an imbalanced class distribution.
- Dataset2: the balanced dataset obtained after applying upsampling, where each class was adjusted to contain 100 images.

5.3 Experimental Setup

The optimal hyperparameters for a fuzzy VGG model are presented in this table 2, which were identified through experimental testing to achieve the best results. Images of a certain size (128 by 128 pixels) can be divided into 21 different classes using the model, an image classifier. The model uses a 50% dropout rate to randomly disable neurons during training, uses Focal Loss to handle potential class imbalance, and makes use of extensive data augmentation by artificially altering the training images to prevent overfitting and improve generalization. With a low initial learning rate of 0.0001, the effective Adam optimizer oversees training, while EarlyStopping controls it.

To ensure reproducibility, all experiments were conducted with a fixed random seed (SEED = 42) for Python, NumPy, and TensorFlow. The dataset was split into 80% training and 20% testing with stratification to preserve class distribution. Data augmentation was applied only to the training set. For robustness evaluation, 5-fold cross-validation was performed on the training set. Training used a batch size of 32 for up to 50 epochs with early stopping and learning rate reduction callbacks. The model was implemented using TensorFlow 2.13 and Keras 2.13 with Python 3.10.

The model's unique FuzzyClassificationLayer replaces a traditional classification layer, which is a key aspect of its architecture. This layer uses cosine similarity as its membership function to determine the degree to which an input belongs to a certain fuzzy cluster. The centers of these clusters are initialized with a Glorot uniform distribution and are trainable, meaning their values are learned during the training process. A temperature parameter of 10.0 controls the sharpness of these fuzzy memberships, influencing the final classification output.

Table 2. Hyperparameters used for the Fuzzy VGG model

Hyperparameter	Value
Input image size	(128, 128, 3)
Number of classes	21
Batch size	32
Optimizer	Adam
Initial learning rate	0.0001
Loss function	Focal Loss ($\gamma = 2.0$, $\alpha = 0.25$)
Dropout rate	0.5
Number of epochs	50
EarlyStopping patience	20
ReduceLROnPlateau	factor 0.5, patience 5, min_lr=1×10^{-6}
Frozen VGG19 layers	First 15 layers
Membership function	Cosine similarity
Centers initialization	Glorot uniform (trainable)
Temperature parameter	10.0
Output	FuzzyClassificationLayer

To further assess the robustness of the proposed FuzzyVGG architecture and to mitigate any potential bias induced by a particular train–test split, a 5-fold cross-validation was additionally performed on the training set. The detailed fold-wise accuracy results are presented in Table 3. The results demonstrate consistent performance across all folds with a low standard deviation, confirming the stability, reliability, and strong generalization capability of the proposed model.

Table 3. 5-Fold Cross-Validation Results on the UC Merced Dataset

Fold	Accuracy (%)
Fold 1	97.14
Fold 2	95.71
Fold 3	96.90
Fold 4	95.95
Fold 5	93.10
Mean	**95.76**
Standard Deviation	**1.44**

5.4 Results

As outlined in the preprocessing step, two dataset configurations were considered for evaluation: the original imbalanced dataset (Dataset1) and the balanced dataset obtained through upsampling (Dataset2). To provide a clear comparison, the classification results obtained using the original imbalanced dataset (Dataset1) and the balanced dataset after upsampling (Dataset2) are summarized in Table4. This joint presentation highlights the effect of class balancing on model performance across all categories.

Table 4. Comparison of classification performance on Dataset1 (Imbalanced) and Dataset2 (Balanced)

Class	Dataset1 (Imbalanced)			Dataset2 (Balanced)		
	Acc.	Prec.	Rec.	Acc.	Prec.	Rec.
Agriculture	0.38	1.00	0.55	1.00	0.95	0.97
Airplane	0.72	0.72	0.72	0.95	1.00	0.98
Baseball diamond	0.70	0.61	0.70	1.00	1.00	1.00
Beach	0.81	0.81	0.81	0.95	1.00	0.98
Buildings	0.88	0.88	0.88	1.00	0.90	0.95
Chaparral	0.85	0.85	0.85	1.00	1.00	1.00
Dense residential	0.81	0.81	0.81	0.83	0.95	0.88
Forest	0.92	0.91	0.92	0.95	1.00	0.98
Freeway	0.49	0.47	0.49	1.00	0.95	0.97
Golf course	0.92	1.00	0.96	1.00	0.95	0.97
Harbor	0.74	0.84	0.77	1.00	1.00	1.00
Intersection	0.80	0.79	0.80	1.00	0.95	0.97
Medium residential	0.78	0.87	0.78	0.85	0.85	0.85
Mobile home park	0.86	0.86	0.86	1.00	1.00	1.00
Overpass	0.84	0.83	0.84	0.95	1.00	0.98
Parking lot	0.76	0.76	0.76	1.00	1.00	1.00
River	0.86	0.87	0.86	1.00	0.90	0.95
Runway	0.85	0.85	0.85	0.95	1.00	0.98
Sparse residential	0.85	0.86	0.85	0.90	0.95	0.93
Storage tanks	0.86	0.86	0.86	1.00	0.95	0.97
Tennis court	0.95	0.95	0.95	0.95	0.95	0.95
Overall	0.80	0.83	0.80	0.97	0.97	0.97

To assess the contribution of the proposed fuzzy-based models, an ablation study was performed by comparing the baseline CNN architectures (VGG16 and VGG19) with our proposed FuzzyVGG16 and FuzzyVGG19 models. The corresponding results are presented in Table 5. Additionally, the training and validation performance of the proposed FuzzyVGG 19 model is illustrated in Figure 6. The curves demonstrate a stable and consistent increase in accuracy over the epochs, while the loss steadily decreases, indicating effective learning and convergence.

Table 5. Comparison of model performance

Models	Accuracy	Precision	Recall	F1-score
VGG16	75%	79%	75%	75%
VGG19	80%	81%	80%	80%
FuzzyVGG16	90%	91%	90%	90%
FuzzyVGG19	97%	97%	96%	97%

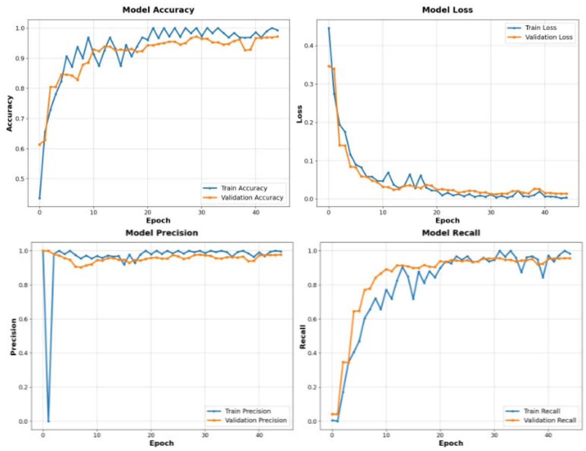

Figure 6. Training curves showing model performance across 50 epochs

6. Discussion

In terms of high-resolution image classification, the Fuzzy VGG19 model represents a major advancement. Our approach develops a more sophisticated and accurate classification system by combining fuzzy logic with a deep convolutional architecture. By giving degrees of membership to several classes rather than a single, strict label, this hybrid approach effectively handles the inherent uncertainty in remote sensing data. This capability is essential for managing slow changes in land types, which strengthens and clarifies the model's decision-making process.

On the UC Merced Land Use dataset, the FuzzyVGG model continuously outperformed traditional VGG models and other existing methods, demonstrating a 15% performance boost and reaching up to 97% accuracy with FuzzyVGG19. This demonstrates the efficacy of our strategy rather clearly. Strong results on a medical dataset demonstrate the model's potent generalization capacity and demonstrate its versatility across a range of fields outside land-use classification. This study demonstrates that integrating fuzzy logic and DL results in a classification system that is more reliable and robust.

6.1 Evaluation against existing approaches

Our FuzzyVGG model is the most successful of the models compared, as table 1 demonstrates. With 97% Accuracy, 97% Precision, 97% F1-Score, and 96% Sensitivity, it attains the top results across all criteria. This performance establishes FuzzyVGG as the best option for this particular land-use categorization job, showing a notable improvement over alternative models such as MobileTransNeXt (96.90% Accuracy) and Inception-V3 (93% Precision).

The primary impact of incorporating fuzzy logic into the FuzzyVGG model goes beyond just achieving high performance. The addition of fuzzy logic provides a crucial contribution to the field of explainable artificial intelligence by enhancing interpretability. Unlike traditional DL models that act as "black boxes," the fuzzy logic component allows the model's decision-making process to be understood and explained. This is achieved by converting complex, numerical data into a set of human-like "if-then" rules. This rule-based transparency makes the model more trustworthy, easier to debug, and provides valuable, understandable insights into the data. In essence, the FuzzyVGG model not only provides highly accurate results but can also explain why it arrived at those results, a critical feature for adoption in high-stakes applications.

6.2 Qualitative Interpretability Analysis and Uncertain Predictions

Examples of uncertain forecasts are shown in Figure 7, where the model gives several land-cover classes similar probabilities. Such uncertainty usually results from varied spatial patterns, especially in residential areas, and from visual similarities between categories (e.g., rivers versus woodlands or beaches). Water bodies encircled by flora, for example, may resemble forest areas to some extent, whereas medium-density residential settings have features in common with both dense and sparse residential layouts. These examples demonstrate inherent dataset overlap and underscore the necessity of decision-making processes that are both uncertainty-aware and explicable. Such predictions represent true semantic ambiguity in remote sensing imagery and encourage the incorporation of interpretability mechanisms to better comprehend class confusion and facilitate dependable deployment in real-world circumstances, rather than signaling model failure.

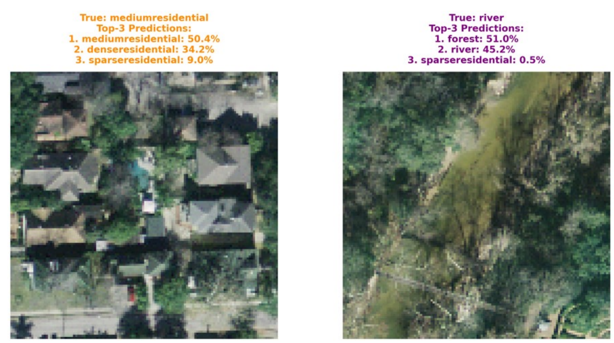

Figure 7. Examples of uncertain predictions on UC Merced test images. Each sample shows the true label alongside the model's three most probable predictions, highlighting ambiguity between visually similar classes.

As a quantitative indicator of model uncertainty, Figure 8 shows the distribution of prediction entropy over the test set. The median (0.194) indicates that most samples have low entropy values, meaning that most predictions are confident. The presence of doubtful cases, which are usually connected to visually confusing or overlapping classes, is revealed by a prominent right-skewed tail with a higher mean entropy (0.328). This distribution supports the efficacy of the suggested fuzzy-based framework in capturing predictive uncertainty and directing interpretability by highlighting the model's capacity to discern between confident and uncertain predictions.

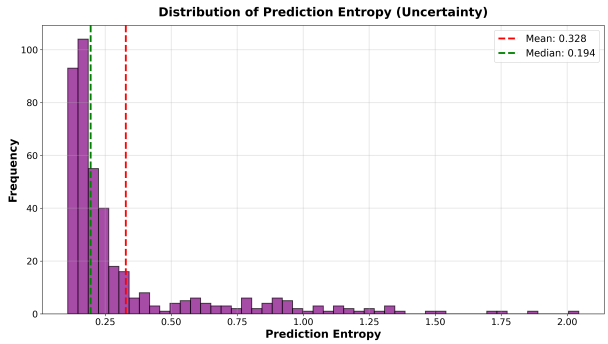

Figure 8. Model uncertainty is shown by the distribution of prediction entropy on the test set. The mean and median entropy values are shown by the dashed lines, which emphasize the majority of low-uncertainty predictions with a tail of unclear cases.

A substantial difference between accurate and inaccurate forecasts can be seen in the confidence distribution. With a tight boxplot range between 0.91 and 1.0 and the great majority concentrated above 0.95 (as seen in the green distribution of the left histogram), accurate forecasts demonstrate exceptionally high confidence (figure 9). On the other hand, wrong predictions show significantly lower and more varied confidence levels, with a wide range ranging from 0.30 to 0.95 (shown in red) and a median of approximately 0.67. In real-world deployment scenarios, where high-confidence predictions can be trusted while low-confidence outputs require manual review, this notable separation between correct and incorrect prediction confidences suggests that the model's softmax output provides a trustworthy uncertainty estimate, making it appropriate for flagging potentially misclassified samples.

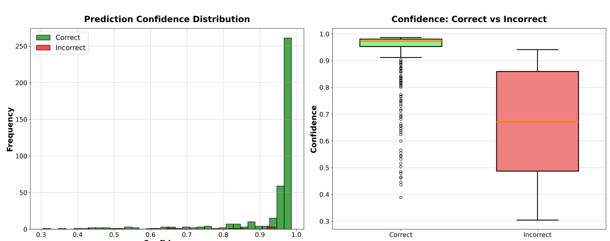

Figure 9. Prediction confidence distribution comparing correct (green) and incorrect (red) classifications

Figure 10 presents typical predictions of the fuzzy membership-based classifier on the UC Merced Land Use dataset. The model performs strongly on visually distinctive categories, such as buildings and beaches, which are identified with high confidence due to their characteristic textures and spatial arrangements. In contrast, the misclassification of intersections as buildings, along with the correct recognition of overpasses, highlights the challenge of differentiating between architecturally and semantically related urban classes. Such behavior is expected in high-resolution aerial imagery due to the substantial visual overlap among urban infrastructure categories, where intersections often incorporate road patterns and building-like structures. Overall, these findings indicate that the proposed model effectively distinguishes between broad land-use classes while reflecting the inherent difficulty of fine-grained urban scene classification involving visually similar elements.

Figure 10. Sample predictions from the fuzzy membership classifier showing correct classifications (green) and misclassifications (red)

6.3 Generalization capability

We extended our architecture to a completely different domain, the classification of malaria cell images, to evaluate the generalization capacity of our Fuzzy VGG model on other benchmark datasets available at ⟨https://www.kaggle.com/datasets/iarunava/cell-images-for-detecting-malaria⟩. The purpose of this test was to show how robust the model is and how it can handle a fresh, different dataset without requiring major changes. The problems of malaria cell imaging datasets include subtle morphological changes between parasitized and uninfected cells that can be hard for traditional methods to detect. The Fuzzy VGG model, despite being trained on satellite imagery, achieved an overall accuracy of 96% on this new task. The classification report below provides a more detailed breakdown of the model's performance on each class (see table 6).

Table 6. Classification Report (Malaria)

Class	Precision	Recall	F1-Score	Support
Parasitized	0.98	0.95	0.96	2756
Uninfected	0.95	0.98	0.96	2756
Accuracy	0.96			
Macro Avg	0.96	0.96	0.96	5512
Weighted Avg	0.96	0.96	0.96	5512

These findings show that our hybrid model's fuzzy classification layer and feature extraction capabilities are not restricted to a particular kind of data. The model's capacity to reliably identify cells infected with malaria is demonstrated by the high precision and recall scores for both classes, particularly the high precision for the "parasitized" class.

The confusion matrix (figure 11) indicates that the model works very well. It showed a significant ability to categorize both parasitized and uninfected cells, properly identifying 2,618 parasitized cells and 2,701 uninfected cells. Only 138 parasitized cells were mistakenly classified as uninfected (false negatives) and 55 uninfected cells as parasitized (false positives) by the model. In a medical application, this low error rate—especially the low number of false negatives—is crucial since it demonstrates how highly accurate the model is at identifying the existence of a condition. Overall, the findings support the model's exceptional accuracy and dependability in differentiating between the two cell types.

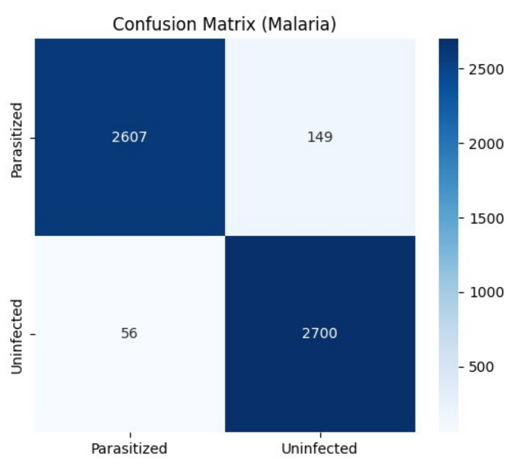

Figure 11. Confusion matrix for the Fuzzy VGG model's classification of malaria cell images

6.4 Code Availability

The implementation of the proposed FuzzyVGG architecture, including the preprocessing pipeline, training configuration, and evaluation scripts, is publicly available to ensure reproducibility of the reported results at: ⟨https://github.com/nawel835/Classification-of-Remote-Sensing-Images.git⟩

7. Conclusion

The study demonstrates that integrating fuzzy logic into the VGG19 architecture significantly improves performance in complex image classification tasks. The proposed Fuzzy VGG hybrid model replaces the standard softmax layer with a fuzzy classification module, enabling better handling of uncertainties in satellite imagery such as illumination variations and ambiguous object boundaries. Experiments on the UC Merced Land Use dataset yielded strong results, with Fuzzy VGG16 achieving 90% accuracy and Fuzzy VGG19 reaching 97%, corresponding to an improvement of approximately 15% over conventional VGG models. Additional evaluations on a medical dataset further highlight the generalization capability of the proposed approach across different application domains. Future work will focus on systematic hyperparameter optimization of both the deep learning and fuzzy components, as well as preparing the model for deployment on resource-constrained platforms.

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Author Contributions

Nawel Slimani: conducted the research and contributed to the writing of the manuscript; Ghazala Hcini: guided the manuscript drafting and ensured the coherence of the overall structure; Imen Jdey: coordinated the development of the work and supervised the methodological aspects; Monji Kherallah: supported the manuscript writing and carried out critical revisions.

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