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AN EFFECTIVE WIDE KERNEL DEEP CONVOLUTIONAL NEURAL NETWORK FOR AUTOMATIC SATELLITE IMAGE CLASSIFICATION

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ABSTRACT
Remote sensing imagery is extensively utilized across various fields, such as ecological observing, agronomy, metropolitan forecasting, and catastrophe managing. Image classification plays a crucial role in driving the rapid progress of remote sensing applications. Despite this, there remains a need for further development in the literature, particularly concerning robust large-scale datasets and models tailored to specific applications. Hence, this manuscript aims to put forth a novel deep learning (DL) model for performing satellite image classification using an enhanced feature learning process. The proposed framework undergoes three essential stages preprocessing, feature extraction, and classification. In the preprocessing stage, the images collected from the raw database are denoised using the Kernel trilateral filtering (KTF) technique to enhance the quality of the satellite images. Then, essential features are extracted and recognized using the Wide Kernel Deep Convolutional Neural Network (WKDCNN) model. Finally, different fields like clouds, deserts, green areas, and water bodies are classified accurately. The proposed method is simulated via the Python platform and various assessment measures like accuracy, F-measure, recall, and precision are analyzed. In the experimental section, the overall accuracy of 99.5%, F-measure of 99%, recall of 99.7%, and precision of 98.9% are achieved by the proposed approach.
Keywords: Satellite Images, Remote Sensing, Deep Learning, Image Preprocessing, Multiclass Classification, Wide Kernel Deep Convolutional Neural Network, Kernel Trilateral Filtering.

I. Introduction
SIC is a vital process in remote sensing, enabling the extraction of meaningful information from large volumes of satellite imagery. Its applications span across numerous domains, including environmental monitoring, urban planning, agriculture, forestry, and disaster management. For instance, in environmental monitoring, satellite image classification helps in tracking deforestation, monitoring water bodies, and assessing the impact of climate change. In agriculture, it aids in crop type identification, yield prediction, and land use analysis, allowing for better management of resources [1]. Urban planners utilize satellite imagery to monitor urban sprawl, assess infrastructure development, and plan for sustainable city growth. Additionally, in disaster management, satellite image classification can provide rapid assessment of natural disasters such as inundations, tremors, and wildfires, facilitating timely emergency response and recovery efforts.
Despite its critical importance, traditional techniques for satellite image classification face significant drawbacks [2]. Many of these methods rely heavily on manual interpretation and predefined feature extraction processes, which are not only laborious but also susceptible to human errors and inconsistencies. Furthermore, these conventional approaches often struggle to cope with the complexity and variability of satellite images, which can include diverse land cover types, varying spatial resolutions, and changing environmental conditions. Another limitation is their inability to effectively handle large-scale datasets, leading to inefficiencies in processing and analysis [3]. These challenges highlight the need for more advanced, automated classification techniques that can offer higher accuracy and scalability.

DL has emerged as a promising solution to address the limitations of traditional satellite image classification methods. With its ability to inevitably acquire composite outlines and topographies from raw data, DL, especially CNNs, can deliver more precise and robust classification results. Unlike conventional methods, DL models do not require extensive feature engineering, making them more adaptable to various types of satellite images [4]. They are capable of handling high-dimensional data and can be trained to recognize subtle differences in land cover types, even under varying conditions such as changes in lighting or seasonality. Furthermore, DL techniques can leverage large extents of categorized data to improve model performance and generalize well to unseen images. This has the potential to revolutionize SIC, enabling more efficient, accurate, and scalable analysis for a extensive assortment of solicitations [5].

Satellite image classification (SIC) plays a critical role in various fields, including ecological observing, metropolitan forecasting, agronomy, and catastrophe controlling. Traditional methods for satellite image analysis often rely on manual interpretation, which can be laborious and disposed to to faults due to the vast extent of data. With the advent of high-resolution satellite imagery, the need for automated, efficient, and accurate classification techniques has become increasingly important. However, existing satellite image classification techniques, including some deep learning models, have certain limitations. One of the key drawbacks is the need for a large, labeled dataset to train deep learning models effectively. In many cases, obtaining such datasets for satellite images is challenging due to the cost and effort involved in manual labeling. Additionally, traditional ML models often struggle with the high dimensionality and variability of SIs, such as variations in lighting, atmospheric circumstances, and periodic variations. This can lead to reduced classification accuracy and generalization issues when applied to new or diverse datasets. Furthermore, while SVMs excel at spatial feature extraction, they may lack the ability to fully capture the temporal dynamics present in satellite images taken over time. This study introduces an improved DL model for classifying multiple scenarios of satellite images accurately.

The foremost contributions of the developed framework are depicted as follows:

- ❖ To propose an innovative hybrid deep learning (DL) model (Op-ACXv3) for classifying multiple scenarios of satellite images.
- ❖ To introduce a Kernel trilateral filtering (KTF) technique for denoising satellite images to enhance the image quality.
- ❖ To present a Wide Kernel Deep Convolutional Neural network-based DL model for extracting the features and recognizing the multiple scenarios of satellite images.
- ❖ To validate the performance of the proposed framework with the conventional technique by evaluating various assessment measures like accuracy, f-measure, recall, PPV, MCC, kappa coefficient, and computation time.

The upcoming sections are organized as follows: Section 2 outlays the related work, Section 3 deliberates over the suggested approaches, Section 4 presents the results and discussion, and Section 5 represents the conclusion of the proposed framework.

II. Literature survey

Kalla et al., [6] identified the satellite image processing (SIP) using the prediction scores of the ML models. The study classified the satellite images into four different classes: green area, desert, water, and cloudy. Various ML models were trained and their performance evaluated on different criteria so as to express their performance. On positive prediction instances, the models did very well in actually correctly predicting and identifying these with almost perfect scores in terms of precision and recall for most of the classes. The limitation here was overfitting on a specific dataset used, which may restrict the generalization abilities of the models on new, unseen satellite images.

Sarangi et al., [7] designed a simple model of satellite image classification using TensorFlow and ImageDataGenerator. It explained the process of preparing data for ImageDataGenerator, a method of loading the data with the function, the way to present the performance of the classification model,

and improving its accuracy. It was aimed to enable readers to comprehend the concepts forming the basics of building a satellite image classification model through the application of DL techniques. The five steps presented in the section provided the foundation for readers to create accurate and efficient SIC models suitable to be used in a broad number of applications. The two models used in this work were MobileNetV3 and EfficientNetB0, which were able to achieve an accuracy of. One of the major limitations lies in the possibility of overfitting of models for the particular dataset in this work, hence limiting their generalizability to any other dataset or real-world satellite images with other characteristics.
ElDien et al., [8] put forth the high-capacity convolutional neural network (CNN) architectures and their variations with large-scale datasets. Various CNN architectures utilizing scaling methods were proposed for the classification of satellite images. The proposed methodology employed spatial information from satellite images to categorize them into four distinct categories. A new modified model, called Deep Global Average Pooling-based Network with Satellite Image Enhancement (DGAPN et-SIE), was introduced to improve the spatial resolution of remote sensing satellite images. The DGAPN et-SIE was designed to learn the spatial features of satellite images more effectively. To enhance image quality, the method incorporated Satellite Image Enhancement using the BM3D technique, an image denoising approach, to reduce noise and improve image resolution. However, the dependence on large-scale labeled datasets for training posed a challenge, as acquiring and labeling such data can be time-consuming and costly. Tumpa et al., [9] introduced the approach using a lightweight parallel CNN (LPCNN) architecture combined with a SVM classifier for the classification of SIs. Initially, preprocessing techniques such as resizing and sharpening were applied to improve image quality. Each branch within the parallel network was designed to target specific resolution characteristics, ranging from low to high. This design enabled the simultaneous extraction of a comprehensive set of features without increasing the network's depth. The LPCNN incorporated a dilation factor to expand the network's receptive field without adding more parameters, and a dropout layer was included to mitigate overfitting. SVM was utilized alongside LPCNN due to its effectiveness in handling high-dimensional features and defining complex decision boundaries, which contributed to an overall improvement in classification accuracy. One of the key limitations was the increased complexity involved in designing and tuning the parallel CNN branches, which could require significant expertise and computational resources.
Kumar et al., [10] conceptualized the Attention U-Net by adding a classification layer. The FC layer of Attention U-Net was used as the base learner for XGBoost, building an efficient framework for classification in remote sensing images (RSIs). This adaptation of Attention U-Net to classification offered benefits, such as using attention mechanisms to concentrate on relevant image regions, which may increase classification accuracy. This approach also employed the multi-scale circumstantial proficiency of U-Net to aid in better solving classification tasks. The method was experimented on effective RSIs of NWPU-RESISC45 and RSI-CB256 datasets. Attention mechanisms improved focus on relevant regions of the image but introduced hyper parameters requiring careful tuning for optimal performance.

2.1 Problem statement

Satellite image classification is essential for extracting valuable information from vast amounts of remote sensing data, with applications ranging from environmental monitoring to metropolitan scheduling and catastrophe supervision. Traditional image classification techniques, however, face several limitations when applied to satellite imagery. These methods often rely on manual feature extraction and predefined algorithms, which are not only time-consuming but also less effective in handling the high variability and complexity inherent in satellite images. For instance, variations in spatial resolution, atmospheric conditions, and seasonal changes can lead to inconsistent results. Additionally, traditional machine learning models, such as SVM and DT, require substantial human intervention to design appropriate features and parameters, making them less scalable and adaptable to diverse datasets. Furthermore, these models struggle with large-scale datasets and may not capture intricate spatial patterns, leading to suboptimal classification accuracy. DL has shown great promise in addressing these challenges, but it also presents its own set of problems. One of the primary issues with deep learning-based satellite image classification is the need for large, labeled datasets to train models effectively. High-quality, labeled satellite data is often scarce and expensive to acquire, posing a significant barrier to developing robust models.

III. Proposed Methodology

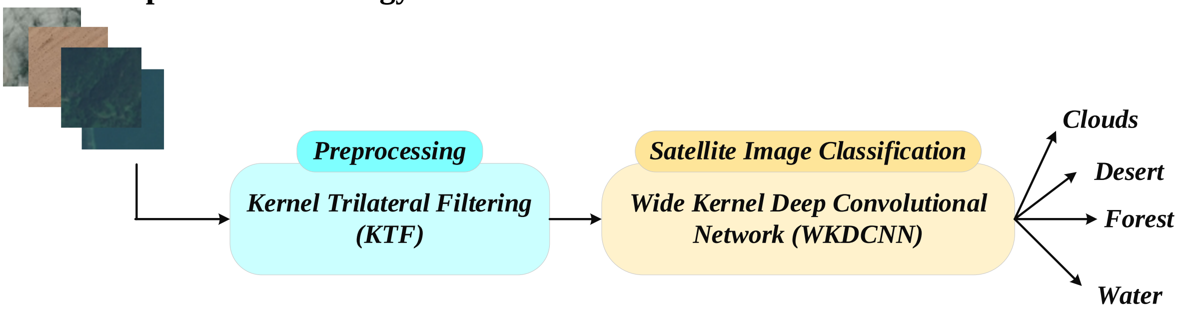

Figure 1: Pipeline of the developed Framework

3.1 Preprocessing Stage

The images collected from the raw database contain high noises that cannot be directly into a proposed model for recognizing the person's identity. Hence, the Kernelized trilateral filtering (K_TF) technique [29] is introduced that does not produce any type of artifacts after removing noise from the image. In the initial stage, the guided image $G_i$with its original imageX_i is considered. Assume $X_v$and $G_v$are the intensity values for the guided image and pixel$b$. The kernel window $k_w$is highly dependent on bilateral filtering and the outcome of K_TF is expressed in equation (1),

$$Y_{K\_TF}(X_i) = \frac{1}{\sum_{a\in k_w} N_\theta^{ab}(G_i)}\left(\sum_{a\in z_r} N_\theta^{ab}(G_i) \times X_b \times (X_b, G_i)\sigma^2\right) \tag{1}$$

Here, $N_\theta^{ab}(G_i)$indicates the updated kernel weight function, and it is mathematically formulated in equation (2),

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$$N_\theta^{ab}(G_i) = \frac{1}{|m|^2}\sum_{m:(a,b)\in z_r}\left(1 + \frac{(G_{ia}-\beta_m)(G_{ib}-\beta_m)}{\sigma_m^2+\epsilon}\right) \tag{2}$$

Here, $\beta_m$indicates the mean, σ_m^2indicates the variance of the local window z_r, and $|m|$defines the total pixel windows. When the parameters $G_{ia}$and $G_{ib}$are similar edges, the weights assumed to a pixel are high. On the other hand, when the parameters $G_{ia}$and $G_{ib}$are opposite edges, a smaller number of weights are determined for the pixel$b$.

3.2 Satellite Image Classification using WKDCNN Technique

The Proposed WKDCNN model is based on 1D CNN, which consists of 1D Convolutional (Conv) layers, activation function (AD), batch normalization (BN), and pooling layers (PL). The initial layer of WKDCNN contains medium-sized Conv kernels that enhance the network model's capability for extracting the features. The integration of AE and WKDCNN can learn the features that are relevant to particular attack types. Except for the initial Conv layer, the Conv layer with its kernel size of three can extend to a deep model and prevent overfitting issues. ReLU-based AF is utilized which can increase the computation speed. It can be mathematically formulated as,

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$$g(y) = max(0, y) \quad (3)$$

The BN layer is highly essential in the WKDCNN, which maximizes the computational efficacy and improves the generalization capability of the network model.

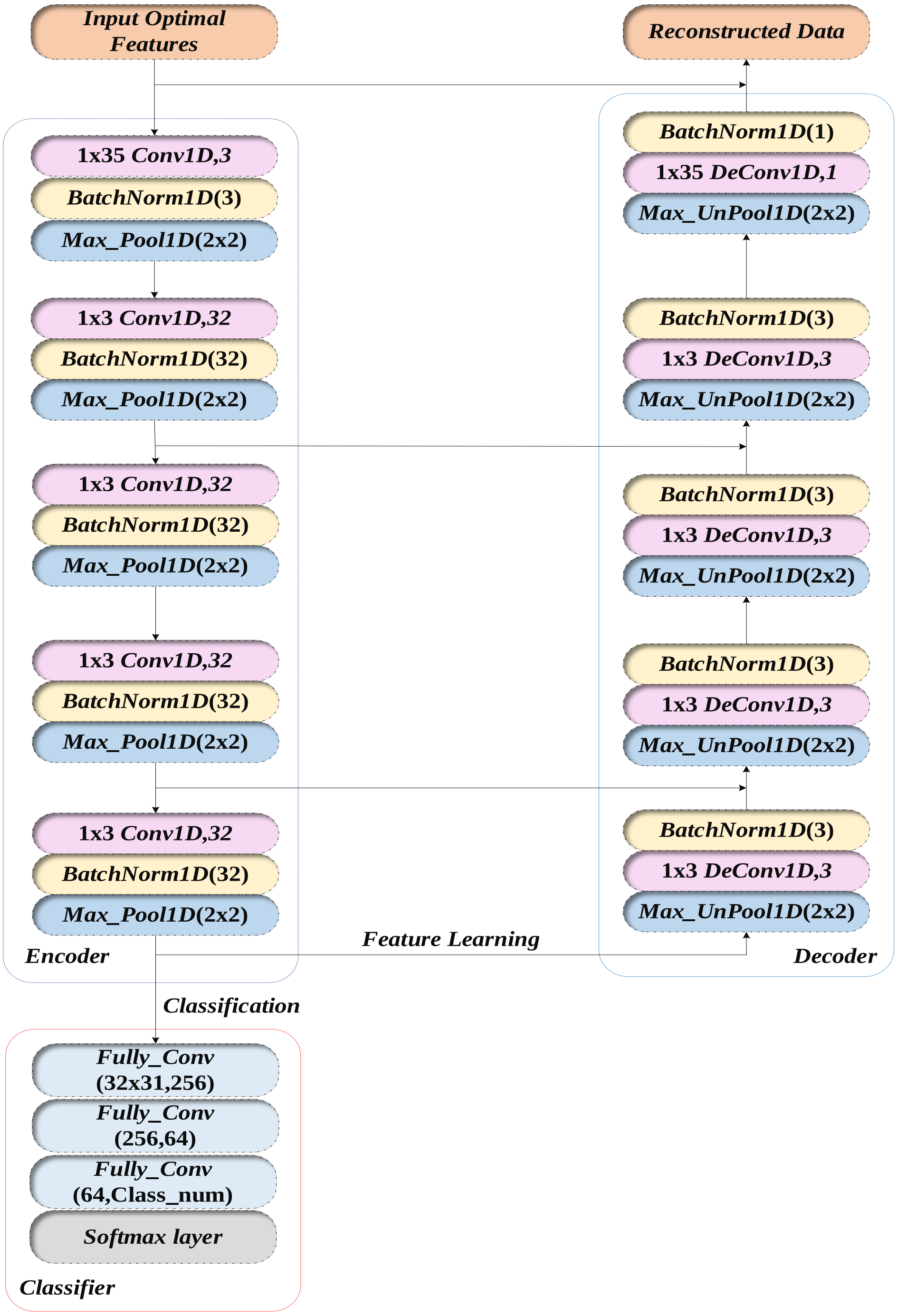

Figure 2: Architecture of the WKDCNN Technique

The PL is the down-sampling operation which minimizes the parameters to minimize the computational complexity. Two different PLs max and average PLs are utilized for the execution process. For the attack classification, Max PLs are utilized in the WKDCNN model. The kernel size of the initial Conv layer is set to 35 and it is utilized for the simulation process.

The Conv-AE model is entirely different from CNN in the decoder phase and it contains deConv layers, up-sampling layers, and BN layers.

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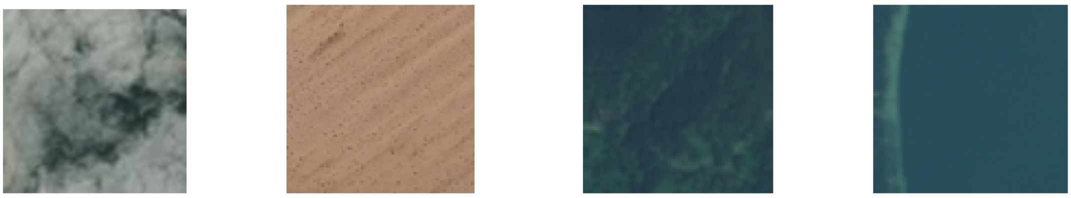

Figure 3: Sample Dataset Images

❖ ***DeConvolution (DeConv) Layer***

The mathematical representation of the DeConv layer is depicted below in equation (4),

$$D_u = \sum Y \otimes \widetilde{W}_u + b_u \qquad (4)$$

Here, $\otimes$indicates the DeConv Operation, $\widetilde{W}_u$deliberates the DeConv kernel, $b_u$signifies the bias, and $u$indicates the number of channels.

❖ ***Up-sampling***

The up-sampling process is the inverse function of PL, which can enhance the DeConv outcome. The mathematical formulation is deliberated below in equation (5),

$$V_p^u = \begin{cases} 0 x \neq j_x \\ Y^u x = j_x \\ p \in [k, 2k] k = 1,2,\ldots. l \end{cases} \qquad (5)$$

Finally, the softmax function is utilized to enforce input features to the range $(0,1)$as the outcome probability. The mathematical expression for the softmax function can be depicted below in equation (6),

$$x_j = \frac{exp(y_j)}{\sum_{u=1}^{M_{calss}} exp(y_j)} \qquad (6)$$

Here, $y$and $x$indicates the outcome and input features, $u$and $j$indicates the outcome neurons of the layers andM_{class}indicates the number of classes. Figure 2 depicts the Architecture of the WKDCNN Technique.

IV. Results and Discussion

The proposed framework is processed and experimented with via the Python platform. The simulation is carried out via the freely accessible Satellite Image Classification [11] database is designed for classifying satellite images into different land cover classes. It contains high-resolution images captured by satellites, representing various geographical and environmental features. Typically, these images include diverse landscapes like forests, urban areas, bodies of water, agricultural lands, and deserts. The dataset is organized into labeled classes, and each class represents a specific type of terrain or land use, providing a broad range of visual data that challenges the model to distinguish between similar features. Figure 3 deliberates the Sample Dataset Images

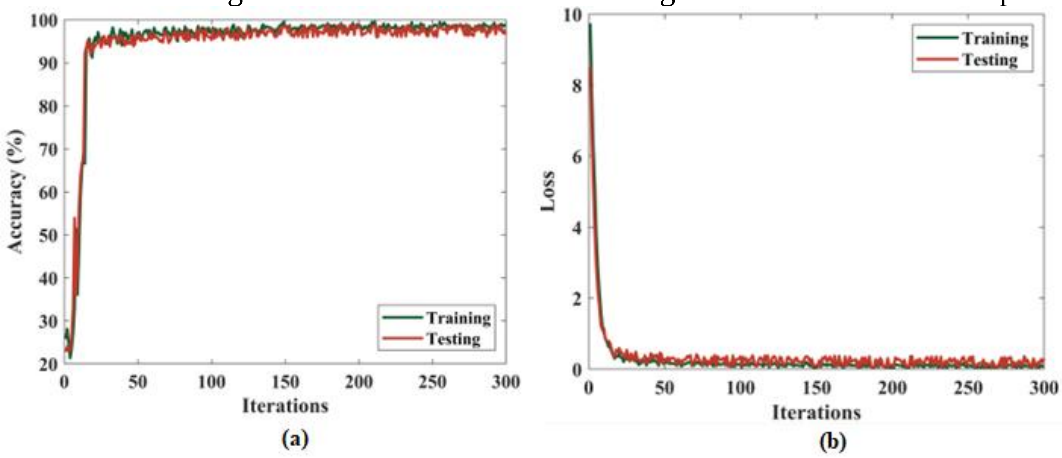

Figure 4: Training and Testing Analysis under different iterations

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4.1 Performance measures

$$Accuracy = \frac{a+d}{a+b+c+d} \quad (7)$$

$$F1 - score = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \quad (8)$$

$$Precision(\%) = \frac{a}{a+c} \quad (9)$$

$$Recall(\%) = \frac{a}{a+b} \quad (10)$$

4.2 Assessing the effectiveness of the Proposed method over conventional studies

In this section, the performance achieved by the developed framework is illustrated and scrutinized via the graphical interpretation.

Figures (4a) and (4b) indicate the Training and Testing Analysis under different iterations. In Figure (4a), the proposed model starts with low accuracy but rapidly improves, stabilizing near 99% accuracy after approximately 50 iterations. Both training and testing curves follow a similar trajectory, indicating that the model generalizes well to unseen data, avoiding overfitting. In Figure (4b), the loss starts high but decreases sharply within the first 50 iterations, eventually stabilizing at a near-zero value. Low loss values signify that the model's predictions are close to the actual target values, and the convergence suggests effective training.

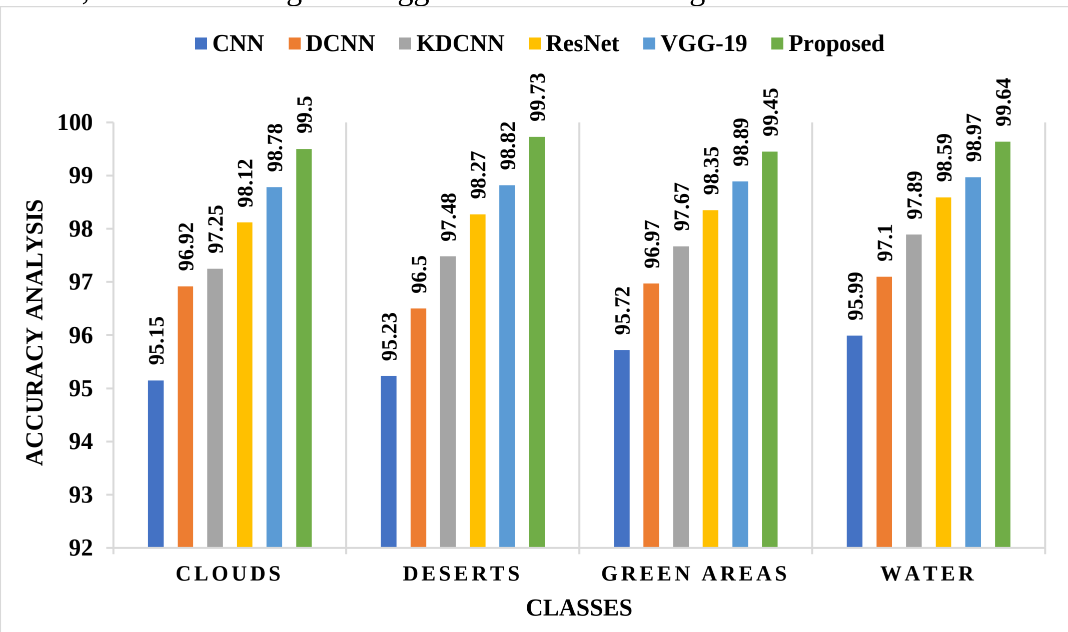

Figure 5: Accuracy Analysis under different Classes

Figure 5 depicts the Accuracy Analysis under different Classes. The graphical illustration shows that the developed WKDCNN technique achieved better performance than other techniques.

Table 1: Performance Analysis of Developed method over existing studies

Techniques Used	**Accuracy**	**Precision**	**Recall**	**F-measure**
Proposed (WKDCNN)	**99.55%**	**98.9%**	**99.7%**	**99%**
CNN	95.15	95.23	95.72	95.99
DCNN	96.92	96.5	96.97	97.1
ResNet	98.12	98.27	98.35	98.59
VGG-19	98.78	98.82	98.89	98.97

Table 1 tabulates the Performance Analysis of Developed method over existing studies. The above table shows that the developed WKDCNN technique achieved better performance than other techniques.

V. Conclusion

The proposed deep learning framework demonstrates a highly effective approach for satellite image classification, utilizing an enhanced feature learning process. By integrating Kernel Trilateral Filtering (KTF) for image preprocessing and the Wide Kernel Deep Convolutional Neural Network (WKDCNN) for feature extraction and classification, the method achieves remarkable accuracy and reliability. The experimental results, with an overall accuracy of 99.5%, F-measure of 99%, recall of 99.7%, and precision of 98.9%, highlight the robustness of the model in accurately classifying diverse satellite image features such as clouds, deserts, green areas, and water bodies. This showcases the potential of the proposed approach for advanced remote sensing applications, paving the way for more efficient and precise image analysis in various fields. One limitation is the reliance on high-quality satellite images for optimal performance; the denoising technique may not be as effective with images containing severe noise or distortions. Additionally, the model's complexity could lead to high computational costs, making it challenging to implement in real-time or resource-constrained environments. Furthermore, the current approach primarily focuses on static images, potentially limiting its effectiveness in applications requiring temporal analysis, such as change detection over time. In future, the developed model is extended to handle multi-temporal or multi-spectral satellite data could improve its applicability to dynamic monitoring tasks. Incorporating transfer learning or fine-tuning techniques may also reduce the need for extensive labeled datasets, improving the model's generalizability to diverse geographical regions.

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