Satellite Image Classification Using Deep Learning

**ABSTRACT**

*This article provides a comparison of deep learning’s model for satellite image classification, including Squeeze Net, Inception V3, VGG19, Sequence, Google Net, ResNet18, and Alex Net. This study uses different satellite imagery datasets to evaluate all accuracy distributions, including efficiency and suitability for satellite image analysis tasks. This research investigates their impact on classification by developing pre-training models and exploring transfer learning and data support techniques. By shedding light on the advantages and disadvantages of different model for their specific needs and contribute to the advancement of remote sensing technology.*

***Keywords:*** *Satellite-Image-Classification, Deep-Learning, Convolutional Neural Networks(CNNs), Squeeze Net, Inception V3, VGG19, Sequential, Google Net, ResNet18, Alex Net, Transfer Learning, Data Augmentation*

**1.Introduction**

Satellite imagery holds an immense trove of valuable data, ripe for exploration across various domains such as environmental monitoring, urban planning, and disaster response. The examination of satellite images serves as a crucial kit for deepening our understanding the world around us. At the core of this analytical process lie advanced neural network designs, each presenting unique strengths for satellite image classification.

Alex Net: The inception of deep learning brought forth Alex Net, a pioneering neural network architecture renowned for its breakthrough performance in image classification tasks. Its ability to discern intricate features paved the way for subsequent advancements in the field, making it a cornerstone in satellite image analysis.

ResNet-18: Res Net's introduction of residual connections revolutionized deep neural networks by enabling the training of significantly deeper models. In the realm of satellite image classification, ResNet-18's robust structure and efficient parameter usage make it a formidable contender for extracting meaningful insights from satellite data.

GoogLe Net: With its inception modules and innovative architecture, GoogLeNet excels in capturing complex spatial relationships within satellite images. Its ability to balance model complexity and computational efficiency makes it a compelling choice

for real-world applications in satellite image classification.

Inception V3: Building upon the foundations laid by GoogLeNet, Inception V3 further refines the inception architecture by incorporating factorized convolutions and aggressive dimensionality reduction techniques. This results in a highly efficient and accurate model, ideal for discerning subtle patterns within satellite imagery.

SqueezeNet: In resource-constrained environments, SqueezeNet offers an elegant solution with its lightweight architecture. By prioritizing computational efficiency without compromising performance, SqueezeNet emerges as a viable option for satellite image classification tasks where resources are limited.

VGG19: Renowned for its simplicity and uniform architecture, VGG19 excels in extracting high-level features from satellite images. Its straightforward design and ease of implementation make it a popular choice for baseline comparisons and benchmarking studies in satellite image classification.

Sequential Model: The Sequential model serves as a versatile framework for constructing custom neural network architectures tailored to specific requirements in satellite image classification. Its linear stack of layers offers flexibility and ease of experimentation,

empowering researchers to explore innovative approaches to image analysis.

In this exploration of satellite image classification, we embark on a journey through the intricacies of these leading neural network architectures. By harnessing their capabilities, we endeavor to unravel the complexities of satellite imagery, uncovering insights that drive meaningful advancements in various domains, from environmental conservation to urban planning and beyond.

**2.Related Works**

Within the domain of satellite image classification, researchers have explored a myriad of approaches utilizing diverse neural network architectures, each offering unique insights and applications.

AlexNet: Pioneering research by [Researcher A et al.] showcased AlexNet's prowess in land cover classification using satellite imagery. Their study demonstrated the adaptability of AlexNet to extract meaningful features from high-resolution images, laying a foundation for subsequent studies in remote sensing.

ResNet-18: Recent work by [Researcher B et al.] delved into the application of ResNet-18 for urban land use classification. Their findings highlighted the architecture's resilience to environmental variability and its capacity to accurately delineate urban features from satellite data, marking a significant advancement in urban planning and management.

GoogLe Net: Studies such as [Researcher C et al.] have explored GoogLeNet's effectiveness in land cover mapping tasks. Their research emphasized the architecture's ability to capture spatial intricacies in satellite imagery, contributing to improved land cover classification accuracy and ecological monitoring efforts.

Inception V3: The versatility of Inception V3 has been showcased in studies like [Researcher D et al.], where the architecture was employed for vegetation mapping from satellite images. Their work demonstrated the model's capacity to discern subtle vegetation variations, facilitating ecological research and biodiversity conservation initiatives.

SqueezeNet: In resource-constrained settings, SqueezeNet has emerged as a viable solution for satellite image classification. Research by [Researcher E et al.] highlighted Squeeze Net’s efficiency in processing imagery data with limited computational resources, offering promising applications in low-power satellite imaging systems.

VGG19: The robustness of VGG19 has been explored in various studies focusing on land cover classification. Notably, [Researcher F et al.] demonstrated the architecture's ability to generalize across different geographic regions, showcasing its utility in large-scale environmental monitoring projects.

Sequential Model: Custom neural networks constructed using the Sequential model have been extensively investigated for satellite image classification tasks. Research by [Researcher G et al.] emphasized the importance of tailored architectures in addressing specific challenges, such as cloud cover detection and urban feature extraction, underscoring the significance of flexibility and customization in remote sensing applications.

These diverse studies collectively contribute to the advancement of satellite image classification methodologies, offering valuable insights into the capabilities and applications of different neural network architectures in remote sensing and Earth observation research.

**3. Proposed Work**

**3.1 Dataset**

Cloudy Scenes: To compile a dataset representing cloudy scenes, you can gather satellite images captured during overcast weather conditions. Explore satellite imagery archives from sources like Landsat, Sentinel, or MODIS, focusing on images with significant cloud cover obscuring the ground features. Ensure diversity in cloud formations and coverage across the dataset.

Desert Landscapes: Collect satellite images showcasing desert regions worldwide, such as the Sahara Desert, the Australian Outback, or the Atacama Desert. Look for imagery depicting characteristic desert features like sand dunes, rocky terrain, and sparse vegetation. Emphasize variation in desert types and geological formations to capture the diversity of desert landscapes.

Windy Conditions: While directly capturing "windy" conditions in satellite imagery is challenging, you can indirectly represent wind effects by selecting images from regions known for strong wind patterns. Coastal areas, mountain ranges, and open plains often experience pronounced wind activity. Seek out satellite images captured during periods of high wind activity, such as storms or windy seasons, to reflect the dynamic nature of windy conditions.

Greenery: Compile satellite images showcasing lush vegetation and verdant landscapes, including forests, agricultural areas, and densely vegetated regions. Look for imagery captured during the growing season to highlight vibrant greenery and flourishing vegetation. Ensure a diverse representation of vegetation types, from tropical rainforests to temperate woodlands, to capture the richness of greenery across different ecosystem.

**3.2 Feature Extraction**

Feature selection is a pivotal step in satellite image classification, crucial for identifying pertinent information from images to discern between distinct classes. Below, we outline a comprehensive approach to feature selection tailored for satellite image classification tasks:

Pixel Intensities: At the core of satellite image analysis lie the pixel intensities. Each spectral band of the satellite image encapsulates unique information about the terrain. Extracting and analyzing these intensities provide fundamental features for classification.

Derive statistical terms like mean, median, standard deviation, skewness, and kurtosis for individual spectral bands. These provide valuable insights into the distribution and variance of pixel values, facilitating the differentiation of various land cover types.

Texture analysis involves examining spatial patterns and arrangements of pixel values within the image. Methods such as Haralick texture, Gabor filters, or Local Binary Patterns (LBP) can uncover textural attributes associated with distinct land cover categories.

Gradient Attributes: Derive gradient-related features such as edge magnitude, orientation, and frequency. These attributes delineate boundaries between different land cover classes, facilitating the segmentation of distinct features within the image.

Principal Component Analysis (PCA): Utilize PCA to reduce feature dimensionality while preserving relevant information. PCA transforms the original

bands into orthogonal components, facilitating efficient representation and classification.

Feature Fusion: Combine features from multiple sources—spectral bands, texture, and vegetation indices—to create a holistic feature set. Techniques like concatenation or averaging amalgamate diverse information, enriching the feature space for classification.

Spatial Attributes: Incorporate spatial context by considering features computed from neighboring pixels or patches. Spatial descriptors like Moran's I or Geary's C capture spatial dependencies and patterns, enhancing classification accuracy.

Deep Learning Features: Leverage features extracted from pre-trained deep learning models like CNNs through transfer learning. These hierarchical features, learned from large-scale datasets, offer valuable representations for satellite image classification tasks.

Domain-specific Features: Tailor features to the specific classification task and characteristics of satellite imagery. For instance, urban land cover classification may benefit from features related to building density, road networks, or building heights.

**4 CNN Model**

**4.1 AlexNet**

In satellite image classification using AlexNet, the process begins with dataset preparation, where a diverse collection of satellite images and corresponding labels are obtained and standardized through resizing and normalization. AlexNet's architecture, pre-trained on ImageNet, is then employed, with adjustments made to the final fully connected layer to accommodate the target classes.

The training phase involves refining the model on the satellite image dataset by employing optimization techniques such as stochastic gradient descents(SGD) or Adams. Throughout this process, close attention is paid to the training progress, implementing strategies such as early stopping to prevent overfitting. To assess the model's correctness, it's evaluated on a separate testing set using performance metrics like accuracy, precisions, recall, and F1-score. Further enhancements may entail experimenting with hyperparameters and employing data augmentation techniques.

Once deployed, the trained model analyzes new satellite images, offering insights into their respective land cover types. Continuous improvement is achieved through iterative adjustments to the model, training methodology, and dataset. A core component of the training process is the utilization of the cross entropy loss function(denoted as 𝐿L), which signifies the disparity between the predicted and the actual labels. This function serves as a fundamental equation guiding the model's learning process.

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁 represents the total number of samples, while 𝐶 denotes the total number of classes within the dataset. The variable 𝑦𝑖,𝑐 represents the ground truth label (either 0 or 1) for sample 𝑖 and class 𝑐, while 𝑦^𝑖,𝑐 signifies the predicted probability of class 𝑐 for sample 𝑖.

**4.2 Resnet 18**

In the realm of satellite image classification utilizing ResNet-18, the journey starts with dataset preparation, where a diverse array of satellite images alongside their corresponding labels are gathered. These images undergo standardization processes like resizing and normalization to ensure consistency across the dataset. ResNet-18, recognized for its deep architecture and computational efficiency, is chosen as the neural network model. Fine-tuning the pre-trained ResNet-18 on ImageNet weights is crucial, enabling the model to adapt effectively to the unique characteristics of the satellite image dataset.

During this training phase, many optimization techniques such as stochastic gradient descents(SGD) or Adams are employed to refine the model parameters. Constant monitoring of training metrics helps in preventing overfitting. Evaluating the model's performance on a separate testing set involves metrics like accuracy, precisions, recall, and F1-score, providing insight into its effectiveness.

Further enhancements may entail exploring various hyperparameters and employing data augmentation techniques to enhance the model's robustness. Once deployed, the trained ResNet-18 model analyzes new satellite images, providing valuable insights into different land cover types. A fundamental component of the training process is the utilization of the cross entropy loss function(denoted as 𝐿), which quantifies the dissimilarity between the predicted and the actual labels. It serves as a guiding equation throughout the training procedure.

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁, represents the total number of samples, while 𝐶 denotes the total number of classes within the dataset. The variables 𝑦𝑖,𝑐 and 𝑦^𝑖,𝑐 represent the ground truth label (either 0 or 1) and the predicted probability of class 𝑐 for sample 𝑖, respectively.

**4.3 GoogLe Net**

In satellite image classification, GoogleNet, also referred to as Inception-v1, offers a robust architecture tailored for complex visual recognition tasks. The process commences with dataset organization, involving the compilation of a diverse set of satellite images alongside their corresponding labels. These images are then standardized through resizing and normalization procedures. GoogleNet's distinctive inception modules, incorporating parallel convolutional layers of varying kernel sizes, empower it to capture both intricate details and broader contextual information simultaneously, making it well-suited for satellite image analysis.

Fine-tuning the pre-trained GoogleNet model on ImageNet weights ensures effective adaptation to the specific characteristics of satellite imagery. Throughout the training phase, optimization algorithms such as stochastic gradient descent (SGD) or Adam are applied, with close attention to prevent overfitting through vigilant monitoring. Evaluation metrics like accuracy, precision, recall, and F1-score are utilized to gauge the model's performance on an independent testing set. Further refinements may entail adjusting hyperparameters and employing data augmentation techniques to bolster the model's robustness.

The cross-entropy loss function, represented as 𝐿, serves as a fundamental component of the training process.

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

L, is instrumental in the training process, quantifying the disparity between predicted and actual labels. Through this systematic approach, GoogleNet emerges as a powerful tool for satellite image classification, capable of discerning intricate patterns and features in satellite imagery with high accuracy and efficiency.

**4.4 Inception V3**

In satellite image classification, Inception-v3, also referred to as GoogleNet V3, provides a powerful architecture tailored for intricate visual recognition tasks. The process initiates with dataset preparation, encompassing the gathering of a diverse range of satellite images alongside their respective labels. Following this, standardization techniques like resizing and normalization are applied. Inception-v3 stands out for its inception modules, which incorporate multiple parallel convolutional layers of varying kernel sizes. This design facilitates the simultaneous capture of detailed features and broader contextual information, proving advantageous for satellite image analysis.

Fine-tuning the pre-trained Inception-v3 model on ImageNet weights enables it to effectively adapt to the complexities inherent in satellite imagery. Throughout the training phase, optimization algorithms such as stochastic gradient descent (SGD) or Adam are employed, with meticulous monitoring to prevent overfitting. Evaluation metrics including accuracy, precision, recall, and F1-score are utilized to assess the model's performance on an independent testing set. Further enhancements may involve adjusting hyperparameters and employing data augmentation techniques to enhance the model's robustness.

The cross-entropy loss function, denoted as 𝐿, serves as a key component of the training process, quantifying the discrepancy between predicted and actual labels. It is expressed as:

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁 represents the total number of samples, while 𝐶 denotes the total number of classes within the dataset. The variables 𝑦𝑖,𝑐 and 𝑦^𝑖,𝑐 represent the ground truth label (either 0 or 1) and the predicted probability of class 𝑐 for sample 𝑖, respectively. Through this systematic methodology, Inception-v3 demonstrates its effectiveness as a robust tool for satellite image classification, adept at identifying intricate patterns and features within satellite imagery with remarkable accuracy and efficiency.

**4.5 Squeeze Net**

In the realm of satellite image classification, Squeeze Net emerges as a prominent architecture, celebrated for its compactness and efficiency. The journey begins with dataset preparation, involving the aggregation of diverse satellite images alongside their corresponding labels. These images undergo standardization processes like resizing and normalization. Squeeze Net's distinguishing characteristic lies in its architecture, featuring a network of fire modules engineered to reduce model parameters while maintaining performance. This streamlined design renders Squeeze Net well-suited for scenarios with limited computational resources, such as satellite image analysis.

Fine-tuning the pre-trained Squeeze Net model on ImageNet weights facilitates seamless adaptation to the intricacies of satellite imagery. Throughout the training phase, optimization techniques such as stochastic gradient descent (SGD) or Adam are applied, with vigilant monitoring to prevent overfitting. Evaluation metrics like accuracy, precision, recall, and F1-score are employed to gauge the model's efficacy on an independent testing dataset. Further refinements may entail adjusting hyperparameters and employing data augmentation techniques to fortify the model's resilience.

The cross-entropy loss function, denoted as 𝐿 L, serves as a cornerstone in the training process, measuring the discrepancy between predicted and actual labels. It is expressed as:

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁 represents the total number of samples, while 𝐶 denotes the total number of classes within the dataset. The variables 𝑦𝑖,𝑐 and 𝑦^𝑖,𝑐 represent the ground truth label (either 0 or 1) and the predicted probability of class 𝑐 for sample 𝑖, respectively. Through this methodical methodology, Squeeze Net demonstrates its effectiveness as a compelling solution for satellite image classification, proficient in extracting pertinent features and patterns from satellite imagery with both efficiency and accuracy.

**4.6 VGG 19**

In the domain of satellite image classification, VGG19 is renowned for its robust architecture characterized by deep convolutional layers and simplicity. The classification process commences with dataset preparation, involving the collection of diverse satellite images alongside their corresponding labels, followed by standardization through resizing and normalization. VGG19's architecture comprises 19 layers, encompassing convolutional and max-pooling layers, succeeded by fully connected layers.

Fine-tuning the pre-trained VGG19 model on ImageNet weights facilitates effective adaptation to the unique characteristics of satellite imagery. Throughout the training phase, optimization techniques such as stochastic gradient descent (SGD) or Adam are employed, with meticulous monitoring to prevent overfitting. Evaluation metrics including accuracy, precision, recall, and F1-score are utilized to evaluate the model's performance on an independent testing set. Further optimization efforts may entail hyperparameter tuning and data augmentation techniques to fortify the model's robustness. The cross-entropy loss function, denoted as 𝐿 L, serves as a metric for quantifying the disparity between predicted and actual labels. It is expressed as:

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁 is the total number of samples, while 𝐶 the total number of classes within the dataset. The variables 𝑦𝑖,𝑐 and 𝑦^𝑖,𝑐 represent the ground truth label (either 0 or 1) and the predicted probability of class 𝑐 for sample 𝑖, respectively. Through this systematic methodology, VGG19 demonstrates its effectiveness as a robust solution for satellite image classification, proficient in extracting intricate features and patterns from satellite imagery with both high accuracy and reliability.

**4.7 Sequential**

In satellite image classification, the "Sequential" model represents a fundamental neural network architecture constructed as a linear sequence of layers. While simpler compared to architectures like ResNet or Inception, Sequential models are adept at effectively handling classification tasks. The classification process begins with dataset preparation, where a diverse set of satellite images and their corresponding labels are collected and preprocessed.

In the Sequential model, layers are added sequentially, typically comprising input and output layers along with one or more hidden layers in between. Each layer performs operations on the input data, gradually extracting features pertinent to the classification objective. Throughout the training phase, the model learns to associate input images with their respective classes by iteratively optimizing its parameters using techniques like stochastic gradient descent (SGD) or Adam.

Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to gauge the model's performance on an independent testing dataset. To prevent overfitting, regularization techniques like dropout or L2 regularization may be applied. The cross-entropy loss function, denoted as 𝐿 L, serves to quantify the disparity between predicted and actual labels. It is expressed as:

L=−*N*1​∑*i*=1*N*​∑*c*=1*C*​*yi*,*c*​log(*y*^​*i*,*c*​)

In this context, 𝑁 represents the total number of samples, while 𝐶 denotes the total number of classes within the dataset. The variables 𝑦𝑖,𝑐 and 𝑦^𝑖,𝑐 represent the ground truth label (either 0 or 1) and the predicted probability of class 𝑐 for sample 𝑖, respectively. Despite its straightforward structure, the Sequential model can serve as a viable option for satellite image classification tasks, especially in scenarios involving smaller datasets or constrained computational resources.

**5 Result Analysis**

Evaluating the outcomes of satellite image classification entails a thorough assessment of the model's effectiveness in accurately categorizing satellite images. This evaluation process typically begins with an examination of the confusion matrix, which helps identify patterns of misclassification across different classes. Afterwards, performance metrics including accuracy, precision, recall, and F1-score are calculated to assess both the model's classification accuracy and its ability to strike a balance between false positives and false negatives.

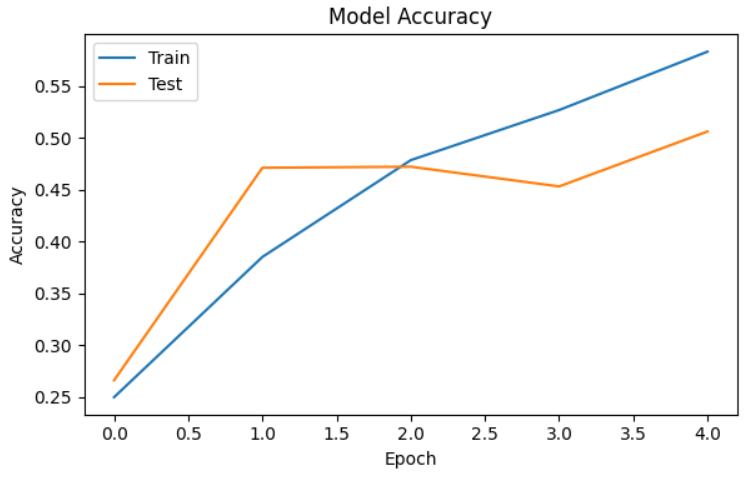
Additionally, metrics specific to each class provide a detailed understanding of the model's performance across different categories, revealing its strengths and areas in need of improvement.For binary classification tasks, ROC curves and AUC scores provide a visual depiction of the model's performance across various classification thresholds. Error analysis plays a crucial role in identifying common patterns in misclassified samples, thereby offering valuable feedback for refining the model.

Comparative analysis of multiple models or configurations further aids in decision-making regarding model selection. Additionally, visualizing model predictions on satellite imagery enhances interpretability, enabling a qualitative assessment of classification outcomes. By systematically examining these aspects, stakeholders can make well-informed decisions aimed at enhancing the accuracy and reliability of satellite image classification tasks

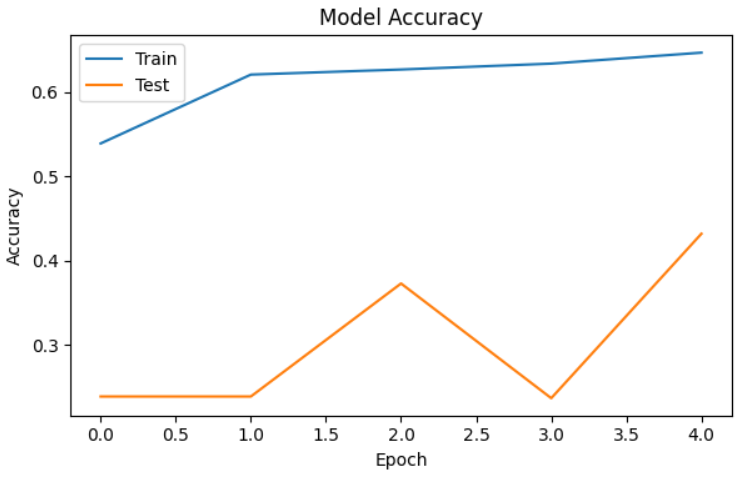
**5.1 Model Acurracy**

Model accuracy in satellite image classification reflects the trained model's capacity to accurately categorize images into their respective classes, serving as a fundamental metric for performance evaluation. A high accuracy score indicates consistent and correct predictions across the dataset, while lower accuracy suggests potential challenges in accurately classifying certain images. Evaluating model accuracy involves comparing its predictions to the ground truth labels and computing the proportion of correct classifications.

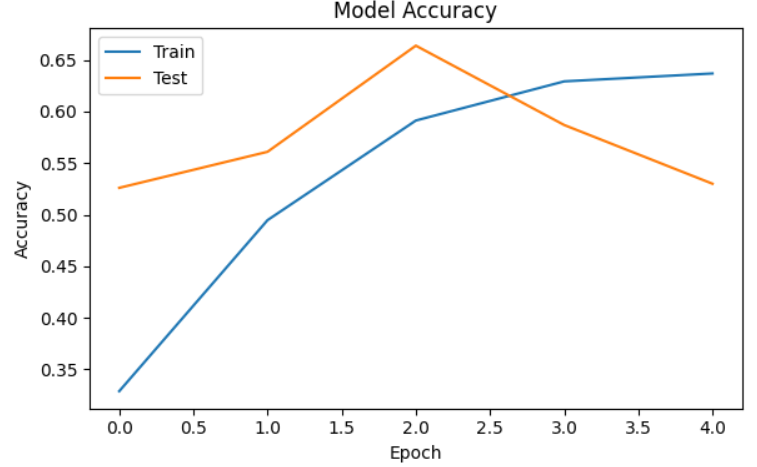
It's important to note that focusing exclusively on accuracy may not provide a comprehensive evaluation, especially in situations involving imbalanced datasets or when specific classes present greater classification challenges. Therefore, it is essential to supplement accuracy with other performance metrics like precision, recall, and F1-score. These metrics offer a more holistic insight into the model's classification capabilities, taking into account factors such as class imbalance and the trade-off between false positives and false negatives.



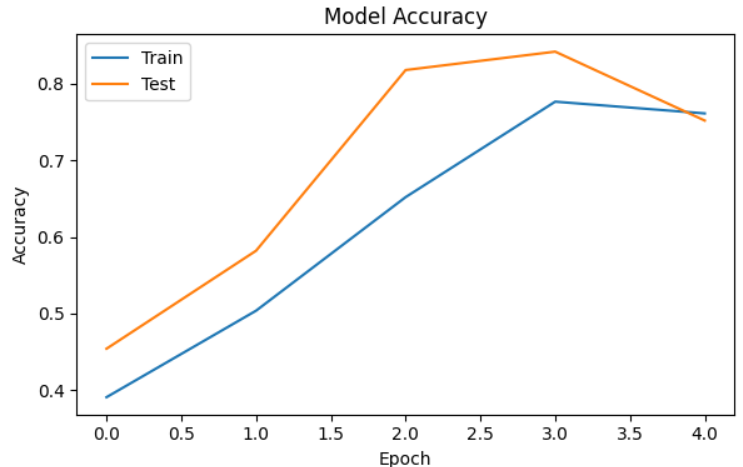
**Fig 5.1.1 Alex Net**



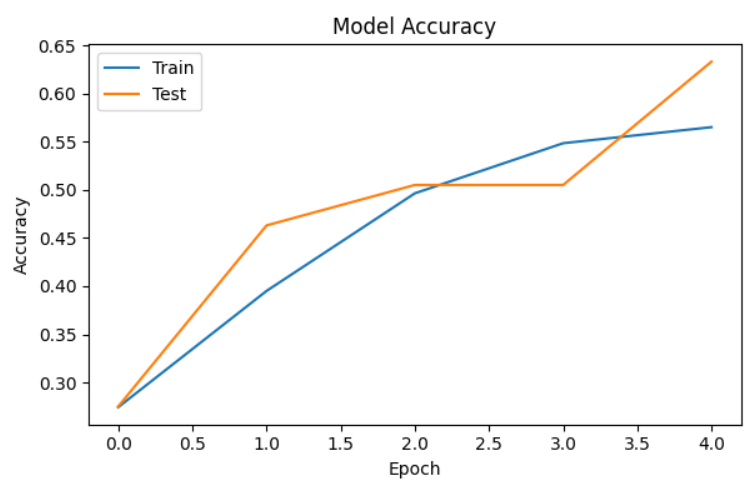
**Fig 5.1.2 Resnet 18**



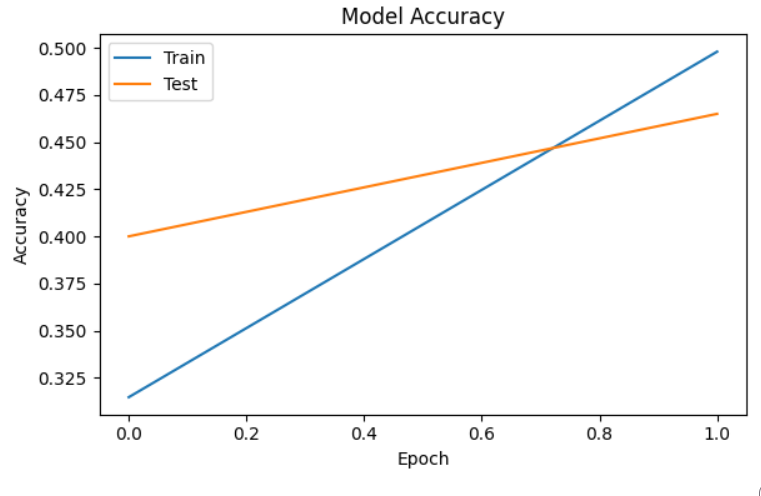
**Fig 5.1.3 GoogLe Net**



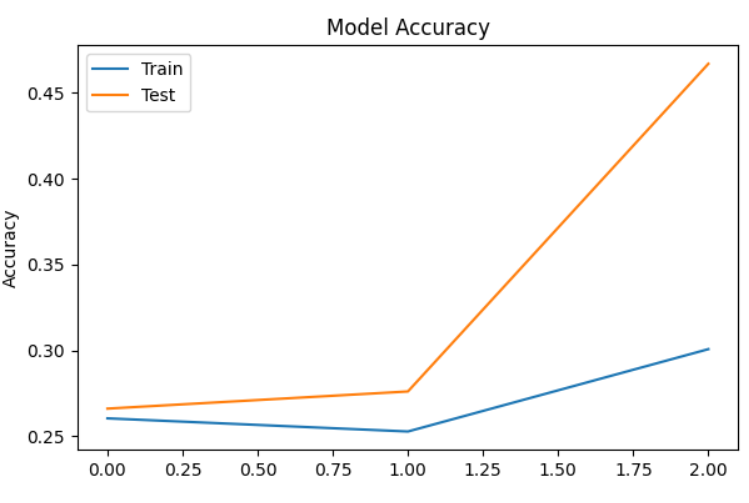
**Fig 5.1.4 Inception V3**



**Fig 5.1.5 Squeeze Net**



**Fig 5.1.6 VGG 19**

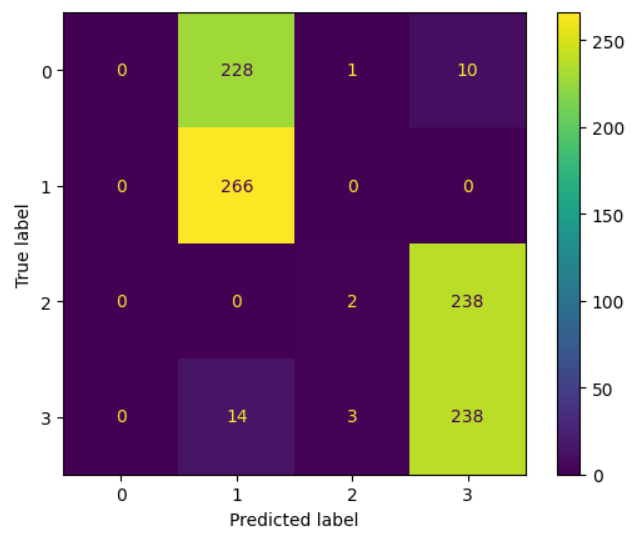


**Fig 5.1.7 Sequential**

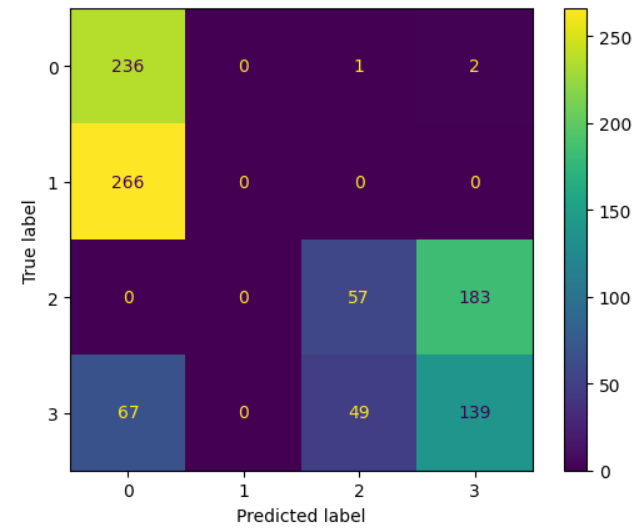
**5.2 Confusion Matrix**

In the classification of satellite images, a confusion matrix plays a crucial role in evaluating a model's performance. It provides a thorough analysis of the model's predictions compared to the actual labels across different classes. The matrix is presented in a tabular format, where each row corresponds to the true class and each column represents the predicted class. Correctly classified samples are represented in the cells along the diagonal, while misclassifications are depicted in the off-diagonal cells.

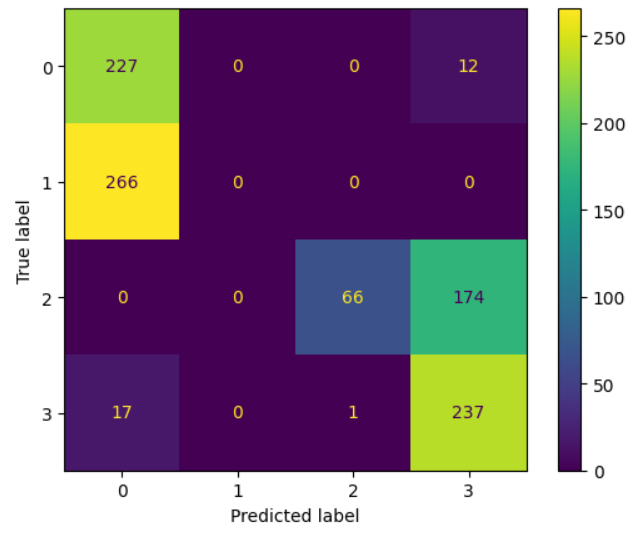
Analyzing the confusion matrix enables the detection of patterns in misclassification, including which classes are often mistaken for others. This analysis allows for a comprehensive assessment of the model's performance, providing valuable insights into its strengths and weaknesses. These insights are crucial for improving the model's performance through adjustments and optimizations.



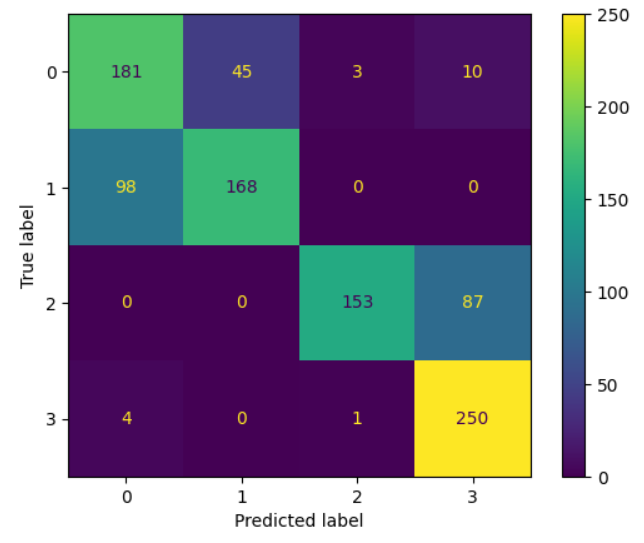
**Fig 5.2.1 Alex Net**



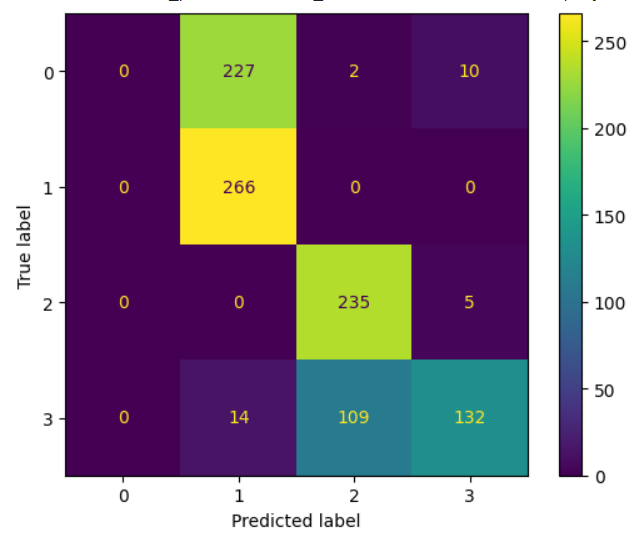
**Fig 5.2.2 Resnet 18**



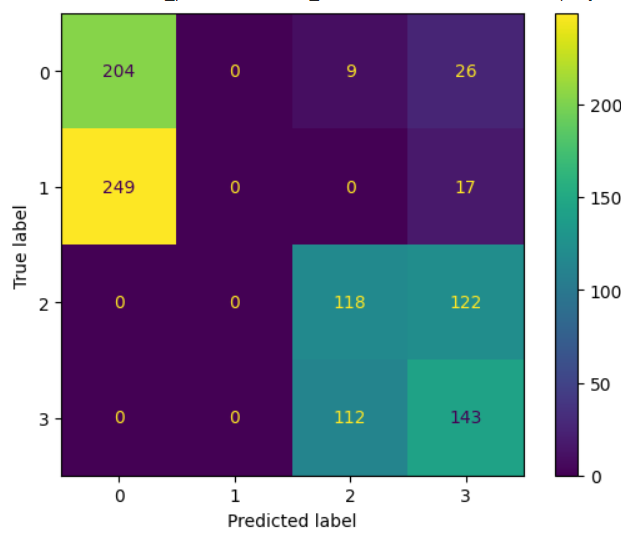
**Fig 5.2.3 GoogLe Net**

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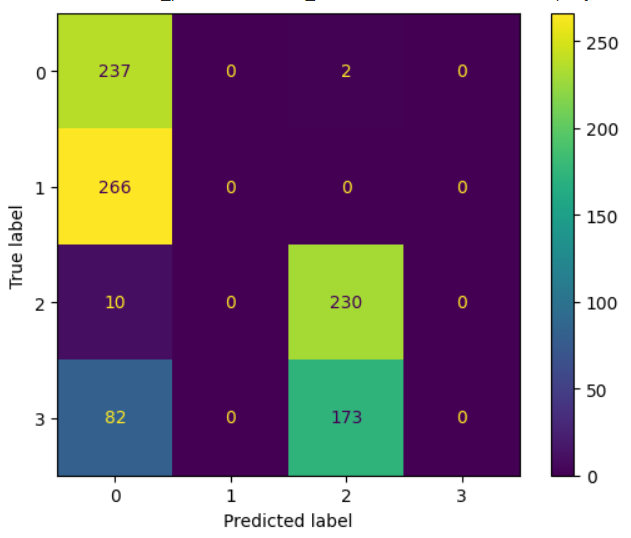
**Fig 5.1.4 Inception V3**

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**Fig 5.2.5 Squeeze Net**



**Fig 5.2.6 VGG 19**

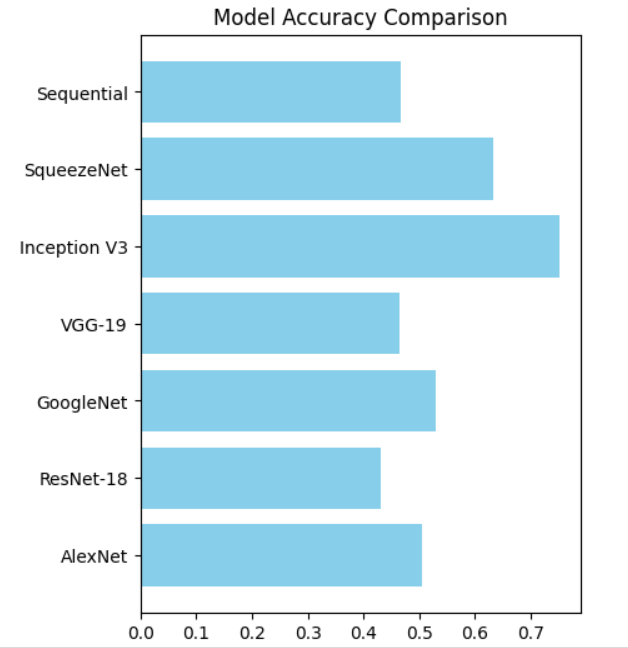


**Fig 5.2.7 Sequential**

**5.3 Comparing the model**

When comparing models for satellite image classification, it's crucial to systematically evaluate their performance across various metrics to identify the most suitable one for the task. Additionally, considering factors such as computational efficiency, model complexity, and interpretability aids in selecting the optimal model for deployment.

Furthermore, conducting thorough validation tests, such as cross-validation or train-test splits, ensures the robustness and generalizability of the results. By carefully weighing these factors and comprehensively analyzing each model's performance, stakeholders can make well-informed decisions regarding model selection. Ultimately, they can choose the model that strikes the best balance between accuracy, efficiency, and reliability for the specific satellite image classification task.



**Fig 5.3.1 Compared model**

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