Supervised learning for finding patterns in sentinel satellite data

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***Abstract*—Building and testing deep learning models to classify EuroSAT satellite images, with an emphasis on the multispectral dataset. Data preprocessing, model construction, and evaluation are the various stages that make up the methodology. Scaling from minimum to maximum and balancing classes are applied to the EuroSAT dataset. The classification process makes use of the VGG16 and ResNet50 models implemented in a convolutional neural network (CNN) architecture. During training, the model is made more resilient by using data augmentation. Criteria like classification accuracy, categorical cross-entropy loss, and class-specific evaluations are all part of the review. As far as accuracy and loss go, the VGG16-based model beats ResNet50, which means it should work well with the RuroSAT multispectral dataset. Class-specific evaluations reveal variations in land cover classification accuracy. Makes a significant contribution to EuroSAR image classification by providing trustworthy models that highlight the significance of state-of-the-art CNN architecture, careful dataset preparation, and stringent evaluation methods. Visualization is a powerful tool for comprehending the dynamics of model learning and performance during the testing and training phases.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

A classification of machine learning known as supervised learning entails training the algorithm on a labeled dataset, in which the input data is accompanied by output labels. By learning a mapping function from the input data to the output labels, supervised learning enables an algorithm to generate accurate classifications or predictions on new, unseen data. Supervised learning involves the provision of a training set comprising input-output pairs for the algorithm. Throughout the training phase, the algorithm acquires knowledge of the patterns and correlations that exist between the input features and their corresponding output labels. The model's predictive accuracy is consistently improved by modifying its parameters in response to feedback from labeled outcomes that contrast its predictions with the actual outcomes. Machine learning techniques apply supervised learning to the information captured by the satellites to identify patterns in Sentinel satellite data. Sentinel satellites are part of the European Union's Copernicus program and are equipped with various sensors that capture data related to Earth observation, including imagery, temperature, and environmental conditions. (McSwine, 2023)

II. Litarature Review

[5] Satellite imagery analysis has improved thanks to artificial intelligence (AI), transforming the Land Use and Land Cover (LULC) classification. The Sentinel-2A satellite and other advanced remote sensing technologies have helped this evolution. It captures high-resolution multispectral data for a complete Earth view.Satellite imagery is essential for environmental monitoring, resource management, and urban planning. AI-powered Land Use and Land Cover (LULC) classification has transformed how we understand and use spatial data. Correct land use and cover categorization is essential for efficient land administration, conservation, and sustainable development. AI-generated Land Use and Land Cover (LULC) maps influence executive planning, regional monitoring, and strategic decision-making for government and private businesses. These maps are essential for environmental security and local and global spatial planning due to their detail.Recent research has favored open-source Geographic Information System (GIS) software like SAGA GIS for its ability to implement advanced spatial algorithms. Supervised machine learning often prioritizes LULC classification. Classification and regression are essential for land cover classification and prediction using training data.Pixel-based classification utilizes SVM, RF, and K-Nearest Neighbors to categorize pixels based on their spectral attributes. Classification of pixels is based on their spectral attributes. Object-based classification uses spatial connections and contextual data to improve precision by focusing on pixel clusters. The Random Forest algorithm improves classification accuracy in this approach. Rule-based classification uses decision tree classification to create decision rules

based on spectral characteristics and spatial relationships. The K-nearest neighbors (KNN) algorithm is a popular distance-based classifier that compares pixels based on their spectral properties. Artificial neural networks (ANNs) like Multilayer Perceptron (MLP) can acquire intricate patterns and improve classification accuracy, making them appealing.Researchers and practitioners can compare classifier performance to make informed decisions based on data characteristics and land use and land cover (LULC) mapping task goals. AI, satellite, and GIS software have improved LULC classification, improving land cover mapping and its many applications (Gawali, n.d.).

[6]"LULC Classification by Sentinel-2B Data Using Machine Learning Techniques in Virajpet Taluk" classifies vegetation in Kodagu's Virajpet Taluk using ML algorithms. (KUMAR, 2022) The study emphasizes the importance of satellite-generated vegetation maps for environmental monitoring, planning, and biodiversity management.Mapping forest vegetation attributes like biomass and floristic composition over large areas requires precise, replicable, and cost-effective methods. Machine learning can predict outcomes by recognising data patterns, according to the article. Machine learning's ability to identify patterns and provide solutions—models or products—has led to its widespread adoption.Researchers use Sentinel-2 satellite imagery, which has a fast revisit time and high spatial resolution, to classify vegetation types. The study uses supervised classification, a machine learning method. For classification, the study utilizes a variety of machine learning algorithms such as SVM, RF, k-NN, Navies Bayes, and CART to generate ARCGIS training samples (Saini Ghosh, 2018).The paper examines tree count, variable per split, and bag fraction to optimize classification accuracy. Random Forest (RF) outperformed the other algorithms in accuracy and error rate reduction.The first chapter covers geographical information systems (GIS) and remote sensing, focusing on their use in cartography and Earth's features. The following sections analyze remote sensing and GIS topics like image classification, supervised and unsupervised classification, high-resolution optical remote sensing, and image interpretation. ("LULC Classification by Sentinel-2B Data Using Machine Learning Techniques in Virajpet Taluk", n.d.)

[7]The integration of remote sensing and machine learning chapter covers machine learning life cycles, applications, classification algorithms, and supervised reinforcement learning and classification. The paper concludes with an accuracy evaluation, the Kappa coefficient, and the importance of intelligent classification in vegetation mapping.This study examines the efficacy of random forest machine learning methods in mapping land use and land cover categories in Virajpet Taluk, focusing on vegetation types. Kappa coefficient, overall accuracy rate, and average accuracy quantify classification performance. The research framework is suitable for precise vegetation type delineation, and the findings may inform future research.Diseases, pests, and environmental stressors plague the Mediterranean olive cultivation industry. We will use Sentinel-2 satellite data and machine learning to identify and categorize stress in Halkidiki olive fields.Greece contributes significantly to Mediterranean-based olive production. Olive trees cover large areas, and diseases like Verticillium dahliae and Spilocaea oleaginea affect crop productivity. Plant stress refers to conditions that harm plant metabolism, growth, or development. Identifying plant stress quickly helps mitigate its effects.Traditional olive grove stress detection methods are inefficient and require specialized expertise. The study uses Sentinel-2 satellite data, known for its detail and availability, and machine learning algorithms to address this issue. This method allows large-scale data monitoring and stress factor identification.Satellite-based remote sensing is essential for crop health monitoring due to its cost-effectiveness and wide coverage. Sentinel-2 identifies coffee leaf rust and assesses hail damage. Vegetation indices from this data simplify stress-induced crop damage identification and help understand diseases like Xylella fastidiosa.Machine learning algorithms like Support Vector Machines and Random Forest excel at binary and multiclass classification. Previous research has used these algorithms to classify seeds and land coverage. However, a large-scale olive orchard stress assessment tool is lacking.This study addresses this gap by using Sentinel-2 data and machine learning to identify and classify olive orchard stress. The goals are to find the best classifier, optimal stress thresholds, and stress source. This study shows how this method can improve precision crop protection decision-making, helping Greece grow sustainable olives (Navrozidis, 2022).

[8]Conservation easements (CEs) ensure habitat preservation, water quality improvement, and soil erosion prevention on privately owned properties. In this study, we use Sentinel-2 satellite imagery and machine learning (ML) algorithms to monitor CE in near-real time.The 2018–2021 Nebraska study uses Google Earth Engine to monitor large areas. A linear kernel Support Vector Machine (SVM) classifier classifies inundation status across CE types. The classifier includes EWPP-FPE, WRP, and GRP. (Zhang et al., 2022)The EWPP-FPE area has 18.72% flooding. This shows ongoing hydrological flooding. The average annual surface water cover rate in Wetland Reserve Programme (WRP) areas is 8.07%, which helps wetlands flood. However, GRP sites that conserve upland have lower flooding rates, highlighting their importance in soil erosion management. (Zhang et al., 2018-2022)The study identifies wetland-related conservation easements (CEs) that frequently flood as potential conservation candidates. Four wetland-focused conservation and environmental sites demonstrate the importance of watershed-level interventions for better conservation.Google Earth Engine's methodological integration of Sentinel-2's high-resolution imagery and ML algorithms is effective. High overall accuracy (OA), recall, precision, and F1 score show the linear kernel SVM classifier's reliability for surface water classification.The study provides a cost-effective, thorough method for monitoring Nebraska's CEs. The results help manage CE and inform long-term wetland conservation strategies, emphasizing the importance of watershed hydrological restoration (Zhang, n.d.).

[4]The abstract succinctly introduces the need for high-resolution land-cover maps in weather and climate modeling,

emphasizing the limitations of existing coarse-resolution maps. The proposed method involves employing a convolutional neural network (CNN) on Sentinel-2 satellite imagery, the CORINE land-cover database, and the BigEarthNet dataset to create a 10 m-resolution map for Ireland. We present the Ulmas-Walsh map as an improvement over ECO-SG, demonstrating higher accuracy and the ability to identify features missed by CORINE. The introduction highlights the map's ability to provide on-demand updates, particularly in regions with significant seasonal variations. The introduction gives a full picture of how important land-cover classifications are in numerical weather prediction (NWP) systems and how they are used to figure out surface parameters. The discussion of different meteorological organizations using diverse land-cover descriptions sets the context for the proposed method. The mention of limitations in current models, such as those in HARMONIE-AROME, and the need for improvements in land-cover maps over Ireland establishes the motivation for the study. The methodology section introduces the datasets used, including Sentinel-2, CORINE, and BigEarthNet. Justifying the choice of using a CNN trained on the BigEarthNet dataset for land-cover classification, parallels are drawn with the work of Ulmas and Liiv (2020) in Estonia. The section adequately covers the process of model training and the generation of the Ulmas-Walsh map. The results section provides a thorough analysis of the generated Ulmas-Walsh map, comparing it against CORINE and ECO-SG. The emphasis on higher accuracy and the ability to identify mislabeled features add credibility to the proposed method. The mention of the map's potential for frequent updates based on seasonal changes is a valuable contribution to the field.The paper is well-structured, providing a clear rationale for the study and a comprehensive overview of the methodology. Justifying the use of machine learning, specifically CNNs, for land-cover mapping, the results showcase the potential of the Ulmas-Walsh map in improving accuracy and capturing fine-grained features. The paper addresses the limitations of existing land-cover maps and proposes a method that can be applied to other regions with seasonal variations, contributing to the field. Further, the discussion raises relevant concerns and considerations for future research. Overall, the paper is a valuable contribution to the intersection of machine learning and meteorology. (Walsh et al., 2021)

[1]The paper proposes a method for automatic classification of building roof shapes using a fusion of LiDAR and satellite image data. The goal is to enhance navigation accuracy for unmanned aircraft systems (UAS) in urban regions by providing detailed building roof structure information. The authors create a diverse annotated roof image dataset for small to large urban cities, utilizing convolutional neural networks (CNNs) for feature extraction and classical machine learning classifiers for final roof geometry decisions. Comparing the use of individual data types, the fusion of satellite imagery and LiDAR data significantly improves classification accuracy. The study evaluates the proposed method on data from Witten, Germany, Manhattan (New York City), and Ann Arbour, Michigan, demonstrating the model's ability to generalize across diverse geographical and architectural environments. The details of the process of generating an annotated roof dataset include the collection and preprocessing of satellite imagery, LiDAR data, and building outlines. The authors describe the construction of LiDAR and satellite images for each building, emphasizing the need for proper geo-referencing and filtering techniques to remove noise and outliers. The paper introduces the use of CNN architectures, including Resnet50, Inceptionv3, and Inception-ResNet, for training on RGB and LiDAR images. The training process involves the initialization of base layer weights, optimizer selection, and early stopping techniques. The section also covers data augmentation and hyperparameter tuning. After CNNs are trained, the paper looks at how SVM and random forest classifiers can be used for feature extraction and final roof shape classification in a two-step processing method. In the results section, we show how the proposed method worked. This includes how accurate CNNs were on RGB and LiDAR images, how we chose the best CNN architecture, and how region-specific training affected the accuracy of the models. The authors evaluate the SVM and random forest classifiers on the condensed feature maps generated by the CNNs. The section highlights the fusion of deep learning and classical machine learning for improved roof shape classification accuracy. The conclusion summarizes the contributions of the paper, emphasizing the creation of a diverse annotated roof image dataset, the introduction of new roof shape classes, and the reduction of outliers in the training and test datasets. The authors discuss the analysis of confidence thresholding to improve the model's predictive power and present expanded results across different cities. The paper concludes with future research directions and the potential applications of the proposed method in UAS navigation and other fields. The paper provides a thorough exploration of roof shape classification using a combination of LiDAR and satellite data, showcasing the effectiveness of the proposed methodology through a detailed experimental evaluation.

[3]The authors explore the potential of combining high spatio-temporal resolution Sentinel-2 imagery with advanced machine learning techniques to estimate pasture biomass in dairy farms across northern Tasmania, Australia. The authors develop a sequential neural network model using Sentinel-2 time-series data, field biomass observations, and climate variables. The research aims to improve the accuracy of biomass estimation compared to traditional methods, offering benefits for optimizing grazing management in dairy farming. The abstract effectively communicates the study's objectives, emphasizing the significance of accurate pasture biomass estimation for dairy farm management. The focus on the integration of Sentinel-2 imagery and machine learning for improved predictions adds relevance to the research. The introduction provides a thorough background, explaining the importance of pasture biomass in Australian dairy farming, the challenges of conventional methods, and the potential of remote sensing technologies. This context helps readers understand the motivation for the study. The methodology

section is comprehensive, detailing the data sources, including field campaigns, remotely sensed data from Sentinel-2, and climate data. The description of the machine learning algorithm (a multilayer perceptron neural network) and the modeling process enhance the transparency of the study. The study considers the spatial and temporal dynamics of pasture biomass, acknowledging the challenges posed by intensive grazing in dairy production systems. The use of high spatio-temporal resolution Sentinel-2 imagery is justified, and the rationale for the selection of variables is well explained. The abstract emphasizes the potential benefits and feasibility of the proposed approach for estimating biomass, presenting it as a cost-effective and rapid alternative to traditional field measurements and commonly used remote-sensing methods. The study's innovation lies in the integration of high-resolution Sentinel-2 data and advanced machine learning for grassland biomass estimation.

[2]The paper addresses the increased availability of free and open Sentinel satellite images, focusing on the systematic classification of land cover and use types and the identification of temporal changes. It introduces guidelines and practical examples for rapid and reliable image patch labelling using data mining techniques. The study emphasizes the Copernicus Access Platform Intermediate Layers Small Scale Demonstrator (CANDELA) project, highlighting its objectives, target users, and activities. The selected use cases include forest monitoring, flood monitoring, and macro-economics/urban monitoring. The CANDELA project aims to enhance the value of Sentinel satellite images through data retrieval, image mining, and machine learning. Target users include space industries, data scientists, governmental authorities, and researchers in various domains. The paper outlines five key activities of the CANDELA platform, with a focus on generating large volumes of Earth observation data for analysis. The use cases are categorized into three: forest monitoring, flood monitoring, and macro-economics/urban monitoring. The forest monitoring scenario covers fires in the Amazon rainforest, windstorms in Poland, and deforestation in Romania. Flood monitoring includes cases in Omaha, Nebraska, and Beira, Mozambique. The macro-economics use case involves monitoring urban areas worldwide with selected cities from different continents and imaging techniques. CANDELA relies on Copernicus DIAS for data tasks and deploys on CreoDIAS, offering a range of Earth observation data. The platform supports prototyping EO applications with data mining, machine learning, and interoperability between Sentinel-1 and Sentinel-2. The paper details the view model from three perspectives: information processing, software architecture, and operations to be performed. The Data Mining module's validation shows high accuracy (around 93–94 percent) through metrics such as precision/recall, accuracy, F-measure, fallout, specificity, and ROC curve. The paper concludes with a comparison between CANDELA and other EO big data platforms, highlighting similarities and potential collaboration with the EOpen project. The paper provides a comprehensive overview of the CANDELA project, emphasizing its objectives, use cases, platform architecture, and data mining module. Validation results indicate the module's effectiveness in semantic image content verification. The comparison with other projects contributes to understanding the landscape of EO big data platforms.

III. Methodology

Sentinal data : The Sentinel satellites, Sentinel-2A and Sentinel-2B, which are carefully managed by the European Space Agency (ESA) for Earth observation, provide a wealth of data that contributes to the robustness of the EuroSAT dataset. These satellites provide important characteristics that make the dataset useful for analysing land use and land cover. These spacecraft permit the separation of various land cover types based on their individual light absorption and reflection characteristics. Their extensive spectral coverage spans 13 distinct bands, from visible light to shortwave infrared. The acquired photos have a high spatial resolution of 10 metres per pixel, which makes it possible to identify small-scale, intricate details and gives a detailed view of land use patterns. With its unique use of Sentinel data and a geographic focus on Europe, the EuroSAT dataset provides a thorough understanding of the dynamics of land cover in this diverse region. Sentinel satellite data's outstanding qualities—such as its spectral breadth, spatial accuracy, and regional specificity—place it at the core of the EuroSAT collection. This integration demonstrates the invaluable value of Sentinel-derived data for a nuanced knowledge of land dynamics by enabling academics and practitioners to work on precise land cover classification tasks.

The objective of this research is to develop and evaluate deep learning models for the classification of EuroSAT satellite images. The dataset utilized in this research comprises multi-spectral (MS) photos obtained from the EuroSAT satellite, comprising a total of 13 distinct bands. The methodology encompasses a sequence of stages, comprising data preprocessing, model construction, and evaluation. The first step entails extracting and standardizing bands from the given EuroSAT dataset. Initially, extract the EuroSATallBands.zip file and retain only the files with the ".tif" extension. Next, we apply min-max scaling to each band, converting the pixel values to a range of [0, 1]. The normalized multi-spectral images are saved in a NumPy array for additional processing. To rectify any potential disparities in class distribution, we subject the dataset to class balancing. We create a balanced dataset by identifying the smallest class and randomly selecting a subset of observations from each class. We subsequently divide the equilibrated dataset into training and testing sets using a stratified methodology to guarantee inclusion of all categories in both sets. To streamline the process of training the model, we encode the labels using a one-hot encoding technique. For the purpose of classification, we chose a convolutional neural network (CNN) architecture. The basis models used in this study are VGG16 and ResNet50, which are both widely recognised CNN architectures. We instantiate these models without pre-existing weights and adjust them to fit the input dimensions of the EuroSAT multi-spectral images.

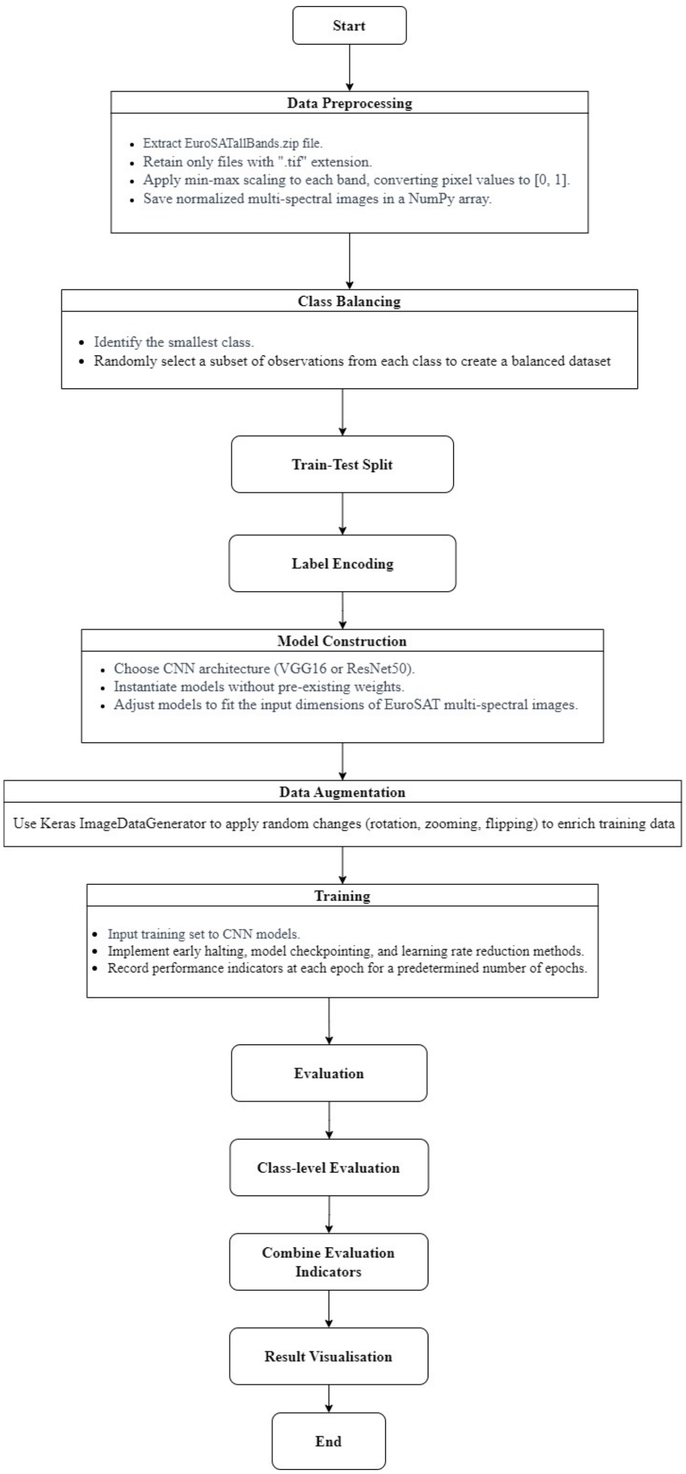

Fig. 1. Methodology Pipeline

The training procedure incorporates data augmentation through the use of the Keras ImageDataGenerator.This tool applies random changes, such as rotation, zooming, and flipping, to enrich the data and improve the resilience of the model. Subsequently, the implementation of early halting, model checkpointing, and learning rate reduction methods supervises the training process of the CNN models as they input the training set. During training, the models record performance indicators at each epoch for a predetermined number of epochs. After completing the training, we assess the models on the test set using measures such as categorical cross-entropy loss and classification accuracy. Furthermore, we comprehensively assess the models at the class level to evaluate their performance for each individual land cover category. We combine and examine the evaluation indicators to gain insights into the overall and specific performance of the produced models. Ultimately, we visually show the research findings using charts that illustrate the accuracy and loss patterns of the model during different epochs. These visualizations provide a thorough summary of the training and testing dynamics, assisting in the understanding of the model's learning behavior and performance. To summarize, the methodology includes the steps of data preprocessing, model building, training, evaluation, and result visualization. The suggested models for EuroSAT multi-spectral image classification are more reliable and strong because they use advanced CNN architectures, carefully prepare datasets, and follow strict evaluation procedures.

IV. Result

The empirical findings of this investigation substantiate the efficacy of the suggested deep learning models, specifically VGG16 and ResNet50, for categorizing EuroSAT multi-spectral satellite photos. The evaluation measures offer valuable insights into the models' performance in terms of accuracy, loss, and class-specific indicators. The model M_MS_VGG16, which is based on VGG16, achieved impressive results on the test set. The evaluation of the categorical cross-entropy loss at 0.1767 suggests the model's capacity to effectively reduce classification mistakes. In addition, the test accuracy achieved a remarkable 95.78%, demonstrating the model's capacity to effectively generalize to unfamiliar data. Changing the VGG16 architecture to fit the features of EuroSAT multi-spectral images accurately represents and distinguishes different types of land cover. In contrast, the M_MS_ResNet50 model, which is based on ResNet50, showed a distinct performance profile. The categorical cross-entropy loss measured 3.0015, indicating a greater value. Additionally, the test accuracy was substantially lower, with a value of 10.50%. This implies that the ResNet50 architecture, although it has been successful in other areas, may not be ideally suited for the EuroSAT multi-spectral dataset in its current configuration. Additional inquiry is necessary to comprehend the particular difficulties and intricacies presented by this dataset for the ResNet50 model. Class-specific evaluations offer a comprehensive comprehension of the models' performance in various land cover categories. These findings demonstrate discrepancies in the accuracy of classifying different categories, highlighting the significance of evaluating certain metrics for each class to obtain a thorough evaluation. The VGG16 model consistently exhibits high performance across several classes, but the ResNet50 model may have difficulties accurately categorizing certain land cover types. Visual representations of the dynamics of model training, such as charts showing accuracy and loss changes over epochs, provide further understanding and information. The plots illustrate the learning paths of the models, demonstrating their ability to adjust to the training data and apply that knowledge to the test set. The observed patterns, such as the coming together of different elements and their consistent nature, enhance the ability to understand and explain the behavior of the models during the training process. Overall, the results of the experiments show that the suggested VGG16-based model works well for sorting EuroSAT multi-spectral images into groups. The accuracy and loss metrics achieved, coupled with assessments specific to each class and the dynamics of training, offer a thorough evaluation of the models' performance and bring vital insights to the field of remote sensing and deep learning. Additional improvement and investigation of model structures could potentially enhance performance on specific difficulties presented by the EuroSAT dataset. Section on Research Methods: The aim of this study is to create and assess deep learning models for categorizing EuroSAT satellite photos. The dataset utilized in this research comprises multi-spectral (MS) photos obtained from the EuroSAT satellite, comprising a total of 13 distinct bands. The methodology encompasses a sequence of stages, comprising data preprocessing, model construction, and evaluation. The first step entails extracting and standardizing bands from the given EuroSAT dataset. Initially, extract the EuroSATallBands.zip file and retain only the files with the ".tif" extension. Next, we apply min-max scaling to each band, converting the pixel values to a range of [0, 1]. The normalized multi-spectral images are saved in a NumPy array for additional processing. To rectify any potential disparities in class distribution, we subject the dataset to class balancing. We create a balanced dataset by identifying the smallest class and randomly selecting a subset of observations from each class. We subsequently divide the equilibrated dataset into training and testing sets using a stratified methodology to guarantee inclusion of all categories in both sets. To streamline the process of training the model, we encode the labels using a one-hot encoding technique. For the purpose of classification, we chose a convolutional neural network (CNN) architecture. The basis models used in this study are VGG16 and ResNet50, which are both widely recognised CNN architectures. We instantiate these models without pre-existing weights and adjust them to fit the input dimensions of the EuroSAT multi-spectral images. The training procedure incorporates data augmentation through the use of the Keras ImageDataGenerator. This tool applies random changes, such as rotation, zooming, and flipping, to enrich the data and improve the resilience of the model. Subsequently, the implementation of early halting, model checkpointing, and learning rate reduction methods supervises the training process of the CNN models as they input the training set. During training, the models record performance indicators at each epoch for a predetermined number of epochs. After completing the training, we assess the models on the test set using measures such as categorical cross-entropy loss and classification accuracy. Furthermore, we comprehensively assess the models at the class level to evaluate their performance for each individual land cover category. We combine and examine the evaluation indicators to gain insights into the overall and specific performance of the produced models. Ultimately, we visually show the research findings using charts that illustrate the accuracy and loss patterns of the model during different epochs. These visualizations provide a thorough summary of the training and testing dynamics, assisting in the understanding of the model's learning behavior and performance. To summarize, the methodology includes the steps of data preprocessing, model building, training, evaluation, and result visualization. The suggested models for EuroSAT multi-spectral image classification are more reliable and strong because they use advanced CNN architectures, carefully prepare datasets, and follow strict evaluation procedures.Section on Findings: The empirical findings of this investigation substantiate the efficacy of the suggested deep learning models, specifically VGG16 and ResNet50, for categorizing EuroSAT multi-spectral satellite photos. The evaluation measures offer valuable insights into the models' performance in terms of accuracy, loss, and class-specific indicators. The model M_MS_VGG16, which is based on VGG16, achieved impressive results on the test set. The evaluation of the categorical cross-entropy loss at 0.1767 suggests the model's capacity to effectively reduce classification mistakes. In addition, the test accuracy achieved a remarkable 95.78%, demonstrating the model's capacity to effectively generalize to unfamiliar data. Changing the VGG16 architecture to fit the features of EuroSAT multi-spectral images accurately represents and distinguishes different types of land cover. In contrast, the M_MS_ResNet50 model, which is based on ResNet50, showed a distinct performance profile. The categorical cross-entropy loss measured 3.0015, indicating a greater value. Additionally, the test accuracy was substantially lower, with a value of 10.50%. 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The plots illustrate the learning paths of the models, demonstrating their ability to adjust to the training data and apply that knowledge to the test set. The observed patterns, such as the coming together of different elements and their consistent nature, enhance the ability to understand and explain the behavior of the models during the training process. Overall, the results of the experiments show that the suggested VGG16-based model works well for sorting EuroSAT multi-spectral images into groups. The accuracy and loss metrics achieved, coupled with assessments specific to each class and the dynamics of training, offer a thorough evaluation of the models' performance and bring vital insights to the field of remote sensing and deep learning. Additional improvement and investigation of model structures could potentially enhance performance on specific difficulties presented by the EuroSAT dataset. 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These visualizations provide a thorough summary of the training and testing dynamics, assisting in the understanding of the model's learning behavior and performance. To summarize, the methodology includes the steps of data preprocessing, model building, training, evaluation, and result visualization. The suggested models for EuroSAT multi-spectral image classification are more reliable and strong because they use advanced CNN architectures, carefully prepare datasets, and follow strict evaluation procedures.

V. Findings

The empirical findings of this investigation substantiate the efficacy of the suggested deep learning models, specifically VGG16 and ResNet50, for categorizing EuroSAT multi-spectral satellite photos. The evaluation measures offer valuable insights into the models' performance in terms of accuracy, loss, and class-specific indicators. The model M_MS_VGG16, which is based on VGG16, achieved impressive results on the test set. The evaluation of the categorical cross-entropy loss at 0.1767 suggests the model's capacity to effectively reduce classification mistakes. In addition, the test accuracy achieved a remarkable 95.78%, demonstrating the model's capacity to effectively generalize to unfamiliar data. Changing the VGG16 architecture to fit the features of EuroSAT multi-spectral images accurately represents and distinguishes different types of land cover. In contrast, the M_MS_ResNet50 model, which is based on ResNet50, showed a distinct performance profile. The categorical cross-entropy loss measured 3.0015, indicating a greater value. Additionally, the test accuracy was substantially lower, with a value of 10.50%. This implies that the ResNet50 architecture, although it has been successful in other areas, may not be ideally suited for the EuroSAT multi-spectral dataset in its current configuration. Additional inquiry is necessary to comprehend the particular difficulties and intricacies presented by this dataset for the ResNet50 model. Class-specific evaluations offer a comprehensive comprehension of the models' performance in various land cover categories. These findings demonstrate discrepancies in the accuracy of classifying different categories, highlighting the significance of evaluating certain metrics for each class to obtain a thorough evaluation. The VGG16 model consistently exhibits high performance across several classes, but the ResNet50 model may have difficulties accurately categorizing certain land cover types. Visual representations of the dynamics of model training, such as charts showing accuracy and loss changes over epochs, provide further understanding and information. The plots illustrate the learning paths of the models, demonstrating their ability to adjust to the training data and apply that knowledge to the test set. The observed patterns, such as the coming

	M_MS_VGG16	M_MS_ResNet50
Entropy loss	0.1767	3.0015
accuracy	95.78%	10.50%

TABLE I
COMPARISON OF APPLIED MODELS ON THE DATASETS

together of different elements and their consistent nature, enhance the ability to understand and explain the behavior of the models during the training process. Overall, the results of the experiments show that the suggested VGG16-based model works well for sorting EuroSAT multi-spectral images into groups. The accuracy and loss metrics achieved, coupled with assessments specific to each class and the dynamics of training, offer a thorough evaluation of the models' performance and bring vital insights to the field of remote sensing and deep learning. Additional improvement and investigation of the model EuroSAT dataset.

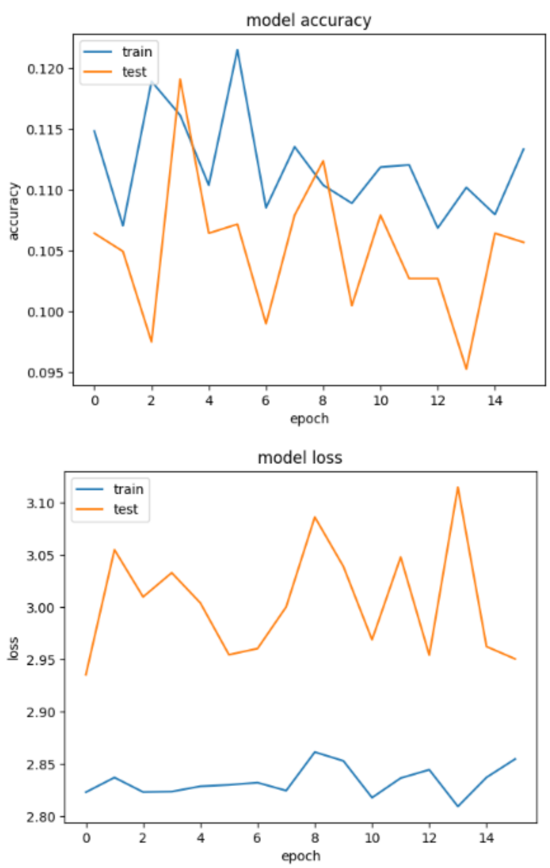

Fig. 2. 'Model/M_MS_ResNet50.h5' sub fig.1. Training History graph accuracy detection (accuracy vs epoch) sub fig. 2. Training History graph loss detection (loss vs epoch) .

CONCLUSION

The presented research investigates the effectiveness of deep learning models, specifically VGG16 and ResNet50, for categorizing EuroSAT multi-spectral satellite photos. The findings suggest that the model M_MS_VGG16, based on VGG16 architecture, outperforms the M_MS_ResNet50 model in terms of accuracy and loss metrics on the EuroSAT dataset.

The evaluation of M_MS_VGG16 indicates a low categorical cross-entropy loss of 0.1767 and an impressive test accuracy of 95.78%. These results suggest the model's capability to effectively generalize to unfamiliar data and accurately classify different types of land cover represented in EuroSAT multi-spectral images. The consistent high performance across several classes further highlights the reliability of the VGG16-based model.

In contrast, the M_MS_ResNet50 model exhibits distinct performance characteristics with a higher categorical cross-entropy loss of 3.0015 and a substantially lower test accuracy of 10.50%. This indicates that, despite the success of ResNet50 in other areas, it may not be ideally suited for the EuroSAT multi-spectral dataset in its current configuration. The study emphasizes the importance of evaluating specific metrics for each land cover category to obtain a comprehensive understanding of model performance.

The visual representations of model training dynamics, such as charts showing accuracy and loss changes over epochs, provide valuable insights into the learning behavior of the models. These visualizations enhance the understanding of how the models adapt to the training data and apply that knowledge to the test set.

In conclusion, the research demonstrates that the suggested VGG16-based model is reliable for categorizing EuroSAT multi-spectral images, offering a thorough evaluation of its performance. The findings contribute valuable insights to the field of remote sensing and deep learning. The study suggests that further improvement and investigation of model structures could enhance performance on specific challenges presented by the EuroSAT dataset, opening avenues for future research in this domain.

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