# Enhanced Land Use and Land Cover Classification Through Human Group-based Particle Swarm Optimization-Ant Colony Optimization Integration with Convolutional Neural Network

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***Abstract*—Reliable classification of Land Use and Land Cover (LULC) using satellite images is essential for disaster management, environmental monitoring, and urban planning. This paper introduces a unique method that combines a Convolutional Neural Network (CNN) with Human Group-based Particle Swarm Optimization (HPSO) and Ant Colony Optimization (ACO) algorithms to improve the accuracy of LULC classification. The suggested hybrid HPSO-ACO-CNN architecture effectively solves the issues with feature selection, parameter optimization, and model training that are present in conventional LULC classification techniques. During the initial phases, HPSO and ACO are crucial in identifying the best hyperparameters for the CNN model and fine-tuning the selection of critical spectral bands. ACO modifies the CNN's hyperparameters (learning rate, batch size, and convolutional layers), whereas HPSO finds the optimal selection of spectral bands. This optimization technique reduces the probability of overfitting while substantially enhancing the model's ability to generalize. Utilizing the selected spectral bands and optimum parameter configuration, the CNN algorithm is trained in the second phase. With Python implementation, this method uses both the spatial and spectral characteristics that the CNN detects to reach an outstanding 99.3% accuracy in LULC classification. The hybrid approach outperforms traditional methods like Deep Neural Network (DNN), Multiclass Support Vector Machine (MSVM), and Long Short-Term Memory (LSTM) in experiments using benchmark satellite image datasets, demonstrating a significant 10.5% increase in accuracy. This hybrid HPSO-ACO-CNN architecture transforms accurate and dependable LULC classification, offering an advantageous instrument for remote sensing applications. It enhances the area of satellite imagery evaluation by combining the advantages of deep learning techniques with optimization algorithms, enabling more accurate mapping of land use and cover for sustainable land management and environmental preservation.**

***Keywords*—Land use and land cover; human group-based particle swarm optimization; ant colony optimization; convolutional neural network; satellite image***

## I. Introduction

A crucial challenge that has significant implications across a range of regions is the accurate categorization of land cover and land use using satellite images. The primary focus of the position is the organized classification and labelling of the surface of the Earth, which serves as a fundamental perspective for understanding and managing the planet's changing landscapes. The designation of urban regions, the identification of infrastructural requirements, and the reinforcement of well-informed choices on land utilization allocation all have been made possible by the LULC categorization, which is crucial for urban planning [1]. This allows for the establishment of effective and environmentally responsible cities. It is a vital instrument in the field of management of the environment for determining how ecosystems are changing, detecting deforestation, and keeping track of the condition of ecosystems in their natural state. In addition, LULC categorization in agriculture provides farmers with knowledge about different crop categories, production, and farming methods, permitting targeted farming methods and boosting food security [2]. Accurate mapping of LULC can help with evaluating susceptibility, organizing for minimizing disaster risks, and adapting quickly to emergencies throughout disaster reconstruction and prevention operations. The capacity of satellite imaging to take wide-ranging images of the exterior of the planet from orbit is crucial for LULC categorization. These images provide us an unusual perspective from which can observe the intricate and constantly shifting topography of the earth [3]. The investigation has access to a variety of data on the Earth's surface, such as specifics about human behaviours, landscape characteristics, and the surrounding environment, by using the camera's array of satellite sensors. A specific component of this categorization, known as land utilization, deals with the numerous ways individuals utilize and communicate with the land, including metropolitan regions, agricultural areas, transportation systems, manufacturing regions, and more. In contrast, land cover describes the physical properties of the Earth's surface independent of human activity, including forests, marshes, lakes and rivers, deserts, and arid areas. Together, the two distinct aspects related to land cover and land use provide an accurate representation of the Earth's surface and provide information regarding the complex interactions between the activities of humans and the surrounding ecosystem [4]. The level of accuracy of assessments made in a variety of disciplines is strongly impacted by how well LULC categorization is done. In urban planning, accurate regulatory control, infrastructure optimization, and support for ecologically friendly techniques are all aided by the definition of land utilization classifications. The capacity to distinguish between diverse kinds of land covers in management of the environment enables investigators to observe wildlife migratory patterns, follow habitat changes, and determine the effects of warming temperatures on ecosystems. In terms of agriculture, LULC categorization enables farmers to engage in decisions based on information, enabling them to select crops more effectively, manage irrigation more effectively, and lessen the impact of diseases and pests. Quick and precise LULC mapping is crucial for response to disasters in order to evaluate destruction, identifying impacted people, and efficiently arrange relief activities [5]. The key component for solving some of the most important issues confronting the global community, from development and deterioration of the environment to food availability and disaster resilience, is proper LULC categorization.

Satellite imagery is now more widely available and of higher quality than ever due to notable technological breakthroughs in the area of remote sensing in recent years. The latest phase of Earth observations has begun as a result of the growth in gathering information, providing an unusual viewpoint on the globe from orbit. Researchers have been able to collect data about the outermost layer of the planet and its changing operations at a degree of complexity never before possible due to the installation of innovative Earth-observing satellites with modern sensors. These satellites continually gather enormous volumes of information that cover a wide range of spectral data, temporal frequencies, and geographical resolutions [6]. Because of this, the field of remote sensing today is distinguished by an extensive collection of extensive and varied satellite imagery, which serves as a significant resource for a wide range of scientific, ecological, and social purposes. Even if the amount of available imagery from satellites is increasing exponentially, there are still many difficult problems it raises. For the information to be used effectively, it requires advanced approaches due to their enormous number and complexity. The fact that these images are multi-spectral and hyperspectral, indicating that they collect data from a broad variety of wavelengths, which include those outside the visible spectrum, presents one of the main obstacles [7]. This spectral variety adds a degree of complexity that necessitates sophisticated analytical methods capable of understanding the subtle differences in the information. Conventional LULC categorization methods suffer to handle this complexity because they are unable to capture the complicated patterns seen in multi-spectral and hyperspectral data. These methods are frequently founded upon manual characteristic engineering and rule-based systems. Traditional LULC categorization techniques frequently depend on hand-made characteristics and pre-established criteria, which may not be sufficient to capture the entire range of variability inherent in satellite images. These methods can be laborious and frequently need expertise in the area for extraction of features. Additionally, rule-based systems' low capacity for adapting to various and changing environments limits their usefulness. The immense prospective of deep learning methods, particularly CNNs, has, in comparison, emerged progressively more understood in the context of the analysis of satellite imagery [8]. CNNs are exceptionally effective at gathering pertinent characteristics from unprocessed information, which enables them to find complex spatial and spectral correlations that can resist manual characteristic engineering. They therefore provide a potential way to improve the accuracy and efficiency of LULC categorization using the vast amount of available satellite information.

The present article introduces a novel method that makes advantage of the interaction between algorithms for optimization and deep learning approaches to address the significant issues provided by the complexities of satellite images and the rising need for precise land use and land cover categorization. In particular, this innovative method combines Convolutional Neural Networks with two potent optimization algorithms—Human Group-based Particle Swarm Optimization and Ant Colony Optimization—to create a hybrid structure designed exclusively for the accurate and reliable categorization of LULC according to satellite imagery [9]. This integrative approach's primary driving force is to handle choosing characteristics and hyperparameter optimization, two crucial aspects of LULC categorization. The correct interpretation of satellite images depends heavily on identifying features, which involves choosing the most significant spectral bands or channels. Each of the categories are equally significant in the context of multi-spectral and hyperspectral imaging, and choosing a suitable combination of channels is essential for lowering distortion and redundancies while enhancing the approach capacity to discriminate between distinct land cover classifications. Human Group-based PSO intelligently selects the most relevant spectral bands to improve the standard of data given into the CNN using a collaborative procedure of optimization motivated by social group characteristics. The subsequent crucial issue the hybrid system addresses is hyperparameter optimization. A wide range of hyperparameters, including learning rates, batch sizes, and the number of convolutional layers, are included in CNNs as algorithms for deep learning. The effectiveness of the simulation is significantly impacted by these hyperparameters, therefore determining the optimum setup is extremely important [10]. ACO is used to adjust these hyperparameters, in order to ensure that the CNN performs at its highest level. It aims to minimize overfitting while optimizing categorization accuracy by balancing model complexities and generalization. This combined strategy transcends the constraints of conventional approaches that depend on manual characteristic engineering and rule-based systems, signalling an important change in LULC categorization. This structure aims to enhance the accuracy and resilience of satellite based LULC categorization, permitting the efficient usage of the extensive and complicated information contained within satellite data. It does this by integrating the effectiveness of optimization methods into deep learning [11].

A crucial and fundamental stage in the field of satellite imagery evaluation, especially in the broader context of classifying land use and land cover, involves characteristic selection. The selection of the appropriate subset of spectral bands is crucial for a number of explanations, not the least of which is that not all spectral bands contributed similarly to the categorization process. Initially reducing data noise is accomplished by carefully choosing the spectral bands. Noise in imagery from satellites can come from a variety of places, such as air interference, sensor constraints, and changes in surface reflectance [12]. Feature selection eliminates or reduces the influence of noisy information by selecting the most pertinent bands, producing more accurate and precise categorization outcomes. This noise reduction improves the categorization model's general durability, making it less sensitive to incorrect classifications carried on by external influences. The process of categorization becomes quicker and more resource-efficient because to the reduction in redundancy, which also improves computing effectiveness. The present study uses Human Group-based Particle Swarm Optimization, a method informed by the combined intelligence of social networks, to carry out the process of characteristic selection effectively [13]. PSO replicates the cooperative behaviour of members of a group, where each member represents a possible mixture of spectral bands. These "particles" move around the spectral band subset search space, continuously modifying their placements in accordance with their individualized and shared understanding. Particles may successfully explore and utilize the search space thanks to PSO's cooperative characteristic by combining spectral bands in techniques that improve categorization accuracy while reducing noise and redundancies.

Convolutional Neural Network architecture tuning of hyperparameters is crucial for obtaining optimal results and strong adaptation as well as to characteristics selection. Hyperparameters include important factors that control whether deep-learning algorithms develop and are built, such as learning rates, size of batches, and the quantity of convolutional layers. These hyperparameters have a substantial impact on how well a CNN can recognize and understand complicated patterns in the information being processed. For example, during optimization, the learning rate determines the phase size and might affect the algorithm's convergence rate and quality. The batch size influences both computational effectiveness and generalization by affecting how the system procedures and modifies parameters during training [14]. Additionally, both the complexity and depth of the CNN is directly determined by the quantity of convolutional layers, with a greater number possibly permitting the collection of more complicated data. Therefore, it is essential to optimize these hyperparameters to ensure that the CNN performs at its optimal level while minimizing the danger of overfitting, which occurs when the algorithm develops excessively specific to the information used for training. This study presents a complete technique that integrates feature selection and hyperparameter optimization, two essential components of satellite image evaluation. The resultant hybrid method, which incorporates CNNs, ACO, and HPSO, has the possibility to transform satellite image processing. The combination of PSO for characteristic selection and ACO for hyperparameter optimization results in an integrated structure that makes use of both the representational strength of deep learning systems and the collective knowledge of optimization algorithms. This innovative method improves categorization accuracy while also strengthening resilience against complicated or noisy satellite imaging information. The hybrid PSO-ACO-CNN strategy that has been developed marks a substantial advancement in the effort to fully use satellite images for important applications in a variety of fields. Land cover and land use categorization skills, which are essential for environmental monitoring, urban planning, agriculture, and disaster management, are set to become more precise and dependable as a result of this technology. The study advances the latest developments in satellite image evaluation by demonstrating the efficacy and effectiveness of this framework via thorough investigations and findings. The potential significance of this study extends beyond the limits of research by providing real-world details that can enable experts to reach better decisions about how to manage the resources of the planet and deal with difficult problems. In short, the study represents a crucial step toward releasing satellite imagery's hidden potential for tackling pressing problems that the planet is currently and in future generations will be confronting.

The Key Contribution of the paper is given as follows:

- The study introduces the EuroSAT dataset, a sophisticated collection of satellite images created specifically for categorizing land cover and usage. This collection includes imagery from satellites with labeled data covering, different categories of land cover and usage across thirteen spectral bands. The massive dataset will be a valuable resource for the remote sensing and computer vision research as it allows for the investigation of deep learning and multimodal fusion techniques.

- The paper presents a unique hybrid optimization approach that combines Ant Colony Optimization for convolutional neural network hyperparameter optimization with Human Group-based Particle Swarm Optimization for feature selection. This technique addresses two important aspects of satellite image processing: selecting the appropriate spectral bands to employ and optimizing the CNN model for best results. The accuracy and robustness of the classification of land use and land cover are increased when these optimization approaches are combined with deep learning.

- The research employs effective image pre-processing techniques, such normalization and histogram equalization, to enhance the quality of the acquired satellite images. These techniques reduce noise and improve system performance while ensuring that the input data to the classification model is of exceptionally high quality.
- By simultaneously optimizing numerous CNN model parameters, such as batch size and learning rate, the research expands on Ant Colony Optimization. The multi-parameter optimization technique ACO-DL enables the CNN to operate at peak efficiency, achieve ideal generalization, and avoid issues such as overfitting. It facilitates the training of the model more easily and leads to improved classification results.
- A comprehensive method that integrates data collection, picture pre-processing, feature selection, hyperparameter optimization, and CNN-based classification into a unified architecture is presented in the study. This comprehensive technique offers an effective way to accurately categorize land cover and use utilizing satellite data, and it has the possibility of revolutionizing the area of satellite image processing for a number of applications, such as urban planning and environmental monitoring.

The rest of the section is organised as shown below. Section II illustrates literature works on Land Use and Land Cover categorization. Section III gives the Problem Statement. Section IV covers the proposed technique for categorization of Land Use and Land Cover from satellite images. Section V illustrates the performance measures and summarises the findings and compares the method's performance to previous techniques. Section VI summarises the conclusion.

## II. RELATED WORKS

The positive consequences of merging Sentinel-1 and Sentinel-2 imagery in the context of land use land cover categorization with U-Net and an evolving understanding of the combinatorial benefits of multi-sensor information fusion are highlighted. The benefits of using both Sentinel-1's radar data and Sentinel-2's optical information for improved LULC categorization have been studied in this field. Sentinel-1's radar information is useful for assessing land surfaces in a variety of environmental circumstances since it can operate in all weather conditions and can be observed through cloud cover. Contrarily, Sentinel-2's optical data offers high-resolution, multispectral data that specializes at catching specific spectral fingerprints, notably in differentiating between different plant varieties and urban characteristics. A potential method has evolved for combining these complementary information sources: U-Net, a deep learning architecture renowned for its capacity for semantic segmentation. In addition to increasing categorization accuracy, it also increases the resilience of LULC mapping by reducing the drawbacks of employing the various sensors separately, such as the sensitiveness of optical information to cloud cover and the sensitivity of radar information to specific varieties of land cover and roughness of the surfaces. Although this fusion strategy has a lot of potential, there are still difficulties in processing the volume of information, integrating multiple information modalities, and efficiently optimizing the deep learning algorithm's parameters [15].

A significant body of research highlighting the essential function of these technologies in evaluating environmental modifications in this important ecosystem has been revealed by the observation of land cover and land use modifications employing GIS and remote sensing methods in human-induced mangrove forest regions in Bangladesh. Investigations in previous years have demonstrated how well Geographic Information Systems technologies paired with remote sensing information, especially from satellites like Landsat and Sentinel, can capture and analyze alterations in mangrove forest cover, extent, and health. These methods have provided benefits including extensive coverage, recurrent gathering of information, and the capacity to distinguish between different land cover classes, that are crucial for tracking changes brought on by humans in mangrove ecosystems. Indicators like the Normalized Difference Vegetation Index and spectral characteristics have been used by researchers to recognize and categorize modifications, facilitating the discovery of elements like urbanization, aquaculture growth, and deforestation that have an impact on these ecosystems. However, issues with information quality, imagine interpretation, and the requirement for fine-scale observation to detect minor modifications still exist. Even yet, the combination of remote sensing and GIS offers a lot of potential for improving the comprehension of the dynamics and preservation of Bangladesh's human-induced mangrove forests [16].

Understanding the link between land cover and urban heat dynamics via remote sensing technologies is important, as demonstrated by the land-cover categorization and its effects on Peshawar's land surface temperature [17]. Previous studies have emphasized the benefits of using satellite imagery, especially Landsat and MODIS information, to map different types of land cover and measure how much that effect affects LST. Studies have shown how important land cover is in controlling urban microclimates, with permeable surfaces like buildings and roads causing higher LSTs that are frequently linked to the urban heat island effects. The influence of modifications to land cover on LST variations in Peshawar has been examined using a variety of categorization approaches, including supervised and unsupervised techniques, together with GIS tools. However, issues with information quality, geographical resolution, and the requirement for highly temporal-resolved statistics to record cyclical temperature fluctuations still exist. However, these studies contribute to the region's initiatives at development strategy and climate adaptation by offering significant understanding into the effects of urbanization-related modifications to land cover and their consequences for Peshawar's thermal environment.

A variety of research has been done on employing remote sensing technologies in order to track and understand the dynamic character of urban settings. This is evident in the study of urban land cover and land use changes employing

Random Forest categorization of Landsat time series information. With its constant and wide-ranging coverage, Landsat satellite information has proven to be a useful tool for tracking modifications to urban land cover over time. Random Forest, a machine learning algorithm, has been used in several research due to its efficacy in categorizing different types of land cover in metropolitan settings. The benefits of Random Forest, including its capacity to manage complicated spectral and temporal structures, account for noisy input, and produce reliable and accurate categorization outcomes, have been demonstrated by these researches. The investigations covered a variety of urban applications, such as detecting land use changes, assessing urban expansion, and characterizing urban heat islands, demonstrating the adaptability of this method. Due to their considerable effects on urban sustainability, management of resources, and quality of the environment, it also emphasizes the rising significance of monitoring modifications to urban land cover and land use. Urbanization, a global trend, has caused fast and occasionally uncontrolled expansion, changing the number of impermeable surfaces, deforestation, and urbanization, among other aspects of the land cover. Wide-ranging effects of these changes include higher energy use, changing microclimates, and ecological disturbances. In order to give statistical knowledge into these urban transitions, academics have increasingly resorted to remote sensing and machine learning approaches like Random Forest. Although the approach has many benefits, there are still some problems, such as the necessity for strong validation techniques, complicated information pre-processing, and modifying variables in the model. The substantial body of research in this area however emphasizes the crucial role that remote sensing and Random Forest categorization serve in dealing with the changing dynamics of urban land cover and land use transformations [8].

The evaluation of deep learning approaches to solve the challenges of satellite imagery evaluation highlights the rising interest in utilizing techniques based on deep learning for land use and land cover categorization in Southern New Caledonia [18]. Convolutional neural networks, in particular, have shown potential in automating LULC categorization activities. They have the capacity to gather features from unprocessed information, adjust to heterogeneous landscapes, and scale to multi-spectral and hyperspectral datasets, among other benefits. The complex and changing landscapes of Southern New Caledonia require effective methods for identifying spatial interdependence within images. The necessity for significant training data that is labeled, problems with the algorithm's interpretability, vulnerability to overfitting, computing resource requirements, and the requirement for balancing the collection of local and contextual data are still problematic. However, deep learning constitutes a substantial development in LULC categorization and has the possibility to enhance the knowledge of and ability to control the dynamics of land cover and land use in Southern New Caledonia.

Machine learning approaches were used to forecast land cover and land use from satellite photos, underscoring the increasing interest in utilizing cutting-edge technology for precise and effective land categorization. For tracking and comprehending modifications to land cover, imagery from satellites has evolved into a vital resource, and machine learning techniques have proven effective instruments in this field [19]. Several machine learning methods have been utilized in multiple studies to estimate the types of land cover and land use from satellite imagery. These methods have a number of benefits, including the capacity to handle big datasets, record complicated spatial patterns, and respond to various topographies. The breadth of research on machine learning-based land utilization forecasts has been demonstrated across a variety of applications, from urban planning and monitoring the environment to agricultural and disaster management. It also emphasizes the significance of precise land-use land-cover forecasts in tackling current issues like urbanization, deforestation, and environmental degradation. The capacity to observe and simulate modifications to land cover is essential for informed decision-making and effective utilization of resources as the global population keeps on growing urbanize and landscapes transform. By simplifying the categorization procedure and supplying accurate and fast data, machine learning approaches have been important in expanding our knowledge of these shifts. The necessity for high-quality information with labels, modelling generalization across diverse locations, and the understanding of complicated machine learning systems remained obstacles regardless their benefits. Nevertheless, the collection of research in this area highlights the possibilities of machine learning approaches in improving the ability to anticipate and efficiently react to modifications in land cover and land use.

An increasing number of researchers are interested in using advanced neural network topologies to improve the precision and effectiveness of land cover categorization operations, as shown by the examination of the deep learning framework for patch-based land cover categorization. Due to their ability to gather pertinent characteristics from image updates deep learning architectures, in particular Convolutional Neural Networks, have become increasingly popularity in recent years. It renders them ideal for classifying land cover from satellite or aerial images [20]. The benefits of CNNs have been demonstrated in research, particularly the capacity to deal with complicated land cover patterns, the capacity to concurrently record spatial and spectral data, and their adaptation to multi-spectral and high-resolution images. This research examined at a variety of deep learning architectures, including model topologies, hyperparameter tuning, and transfer learning, and have shown the way they may be used to achieve the highest possible accuracy in classifying land cover. The also highlights how important precise land cover categorization is for purposes in environmental evaluation, urban development, agriculture, and disaster prevention. For making decisions and policy creation, the capacity to autonomously and accurately classify different kinds of land cover at the patch levels is crucial. In this environment, deep learning architectures, which can handle massive datasets and provide real-time data, are emerging as an innovative technology. The necessity for large amounts of labeled information for training, the ability to interpret of models, and the computing resources necessary for deep network training are still issues. However, the large amount of research in this area shows the enormous potential of deep learning architectures in enhancing the ability to categorizing land cover and addressing important problems with land cover and land use assessment.

The comprehensive extraction of multiscale timing dependency used in the land-cover categorization with time-series data remote sensing images emphasizes the growing significance of using temporal data in land cover assessment. Conventional land-cover categorization frequently employs images from a single date, which could not accurately represent how quickly land cover varies. On the other hand, time-series imagery from satellites, which are often collected over a long period of time, provide an extensive amount of information for comprehending land cover dynamics. Multiscale timing dependency, which takes into account not only the spectrum data but also time-dependent trends and relationships among observations, has been identified by investigators as having potential. Recurrent neural networks and machine learning methods have both been investigated to obtain thorough temporal information that will increase the reliability of land cover categorization. The results of these investigations show the benefits of using time-series information in land cover research, allowing for more accurate monitoring of modifications to land cover, urbanization, agricultural methods, and environmental alterations. The requirement for more study in this field is highlighted by the fact that there are still issues with data pre-processing, handling cloud cover, and dealing with the computing needs of analyzing large time-series datasets [21].

An integrated strategy that combines nature-inspired optimization approaches with modern deep learning methodologies to improve the accuracy of land cover categorization is reflected in the most effective orientation whale optimization algorithm and hybrid deep learning systems for land cover and use categorization. Due to the increasing accessibility of remote sensing information as well as computer resources, conventional land use land cover categorization methods have experienced substantial improvements. A potential optimization method for adjusting the hyperparameters of deep learning systems is the optimum guiding whale optimization algorithm, an extension of the whale optimization algorithm. This algorithm demonstrates increased convergence and optimization characteristics and is motivated by the social behaviour of humpback whales. This method uses spatial as well as temporal data from satellite images in combination with deep learning networks to accomplish accurate LULC categorization. The also highlights the significance of precise LULC categorization in several applications, such as urban planning, environmental surveillance, disaster preparation, and agriculture. Deep learning networks and the best guide whale optimization technique are used to solve the problem of improving complicated models while taking into account the special properties of remote sensing information. There continue to be issues with modelling interpretability, algorithm integration, and the requirement for a large amount of labeled training information. However, this method offers an innovative research area with the possibility of substantially enhance the accuracy and effectiveness of LULC categorization, which would be advantageous to many fields that depend on land cover data for making decisions and policy development [22].

The previously mentioned investigations pertaining to the classification of land use and cover highlight the growing need of using a wide range of remote sensing technologies and sophisticated methodologies to improve the ability to precisely and effectively evaluate the dynamics of land cover. These approaches have demonstrated an enormous amount of potential in terms of their ability to offer comprehensive data on alterations in land use and cover. The effectiveness of these methodologies in documenting changes in land cover and land use through time, for example, has been shown by studies undertaken in places like Peshawar, Southern New Caledonia, and human-induced mangrove forest areas in Bangladesh. Through the utilization of remote sensing technology, researchers have been able to get broad coverage, track alterations in land cover classes, and evaluate the effects of deforestation, urbanization, and aquaculture growth on diverse ecosystems. These methods have great potential to handle modern issues like catastrophe preparedness, urban planning, environmental protection, and agricultural management, where precise land cover data is essential. However, there are several difficulties and disadvantages with these intriguing approaches. The significant need for labeled training information which can be labour-intensive and time-consuming to obtain, particularly for extensive land cover mapping projects is one of the main obstacles. Furthermore, because they might affect the precision and dependability of classification results, the reliability and interpretability of information from remote sensing remain to be a cause for concern. Large time-series dataset management and analysis can provide logistical and technological difficulties. In order to fully realize the potential of these techniques and assure their successful implementation in real-world scenarios where accurate and timely land cover information is critical for well-informed decision-making and efficient resource management it must be essential that these obstacles be addressed.

## III. Problem Statement

From the above literature review it is observed that the most important tasks in environmental monitoring, urban planning, and natural resource management is classifying land cover and land use utilizing satellite information. A critical component of decision-making processes is the correct categorization of land cover kinds, such as forests, urban areas, agricultural fields, and water bodies. The complexity and size of current satellite imaging information is frequently excessive for conventional strategies for land cover and land use categorization to manage [23]. This study suggests a unique method for addressing the issue by fusing the strength of hybrid HPSO and ACO with CNN for land use and land cover categorization. The goal is to create a categorization system that is accurate and effective, capable of autonomously analyzing satellite images and categorizing different types of land cover. By combining PSO and ACO with human input, the optimization procedure is regulated by human knowledge. By combining domain-specific expertise, this "human in the loop" method can produce superior outcomes.

## IV. Proposed HPSO-ACO-CNN

Data gathering, pre-processing, feature selection utilizing a human group based PSO algorithm, and CNN hyper parameter optimization employing ACO constituted the approach used in this study. The process of gathering data includes building the EuroSAT dataset, which consists of 27,000 annotated Sentinel-2 satellite photos representing ten distinct land use and land cover classifications over 13 spectral bands. After data collection, normalization and histogram equalization were used in image pre-processing to improve the quality of the images. PSO was used in feature selection to intelligently identify pertinent spectral bands, while ACO was used to optimize CNN hyperparameters which includes batch size and learning rate. The CNN model, created for LULC categorization, completed training, and optimization was made possible by ACO-DL, a modification of ACO that allows for simultaneous optimization of several parameters. This hybrid approach provides a comprehensive approach integrating optimization approaches with deep learning for efficient satellite image processing. Its goal is to increase LULC categorization accuracy. Fig. 1 shows the overall structure of the proposed framework.

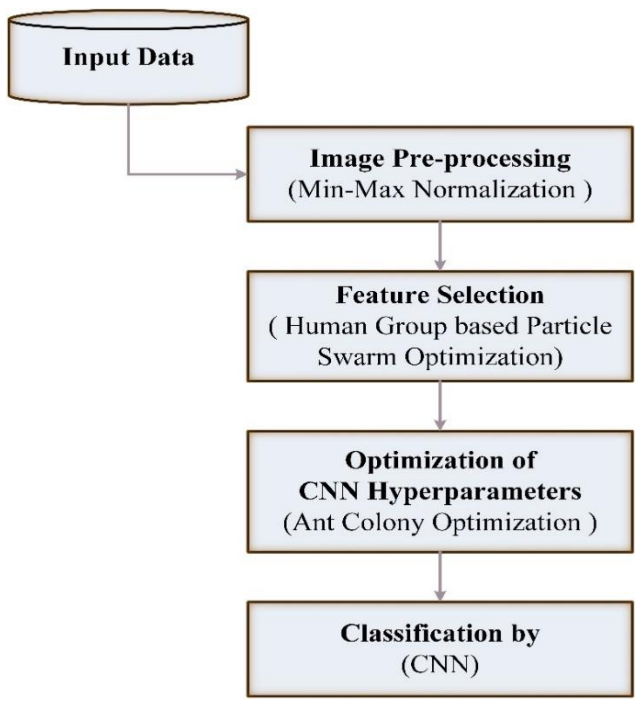


Fig. 1. Overall structure of the proposed framework.

### A. Data Collection

The study presents an innovative set of satellite images for the categorization of land cover and land use. The Sentinel-2 satellite imagery that constitute up the 27,000 annotated images that constitute up the provided EuroSAT dataset depend on an overall of 10 distinct classifications. The patches are 64 by 64 pixels in size. The European Urban Atlas cities were chosen for the study's satellite images1. The given satellite image dataset, which includes thirteen spectral bands and has a significant amount of two thousand to three thousand image patches per class, differs significantly from earlier datasets in that it enables the investigation of multimodal fusion strategies in the overall setting of these bands. If deep neural networks need to be used for categorization, this is a particularly challenging problem. The offered dataset additionally depends on publicly available Earth observation information, opening up a variety of novel real-world applications. In accordance with the coverage in the European Urban Atlas, the areas included in the dataset were collected from cities distributed over thirty different European nations. Additionally, each individual picture patch's geoformation is made accessible to the public together with the labeled dataset EuroSAT. In order to obtain as much variation from the covered land cover and land use classifications as feasible, the study also extracted images taken throughout the year [24][1].

### B. Image Pre-processing using Min-Max Normalization

To improve the quality of the satellite images, normalization and histogram equalization techniques are used after data collection. By altering the range of pixel values, a process known as image normalization, or contrast stretching, one may enhance the visually appealing qualities of satellite-image collection. (1) is a well-known simple formula that expresses the typical scenario of a min-max normalization to generate an additional image spanning from 0 to 1.

$$H_{out} = (H_{in} - Min)\frac{newMax - newMin}{Max - Min} + newMin \qquad (1)$$

Where the original satellite image is denoted as $H_{in}$, the minimum and maximum intensity values, which range from 0 to 255, are represented as $Min$ and $Max$, respectively, the image after min-max normalization is denoted as $H_{out}$, and the new minimum and maximum values are denoted as $NewMin$ and $newMa$x. The histogram equalization approach is then applied to enhance the image quality without eliminating any of the image's borders, patches, or points. The histogram equalization approach adjusts the normalized images' mean brightness to the allowable range's midpoint, while maintaining the original brightness prevents intrusive artifacts from appearing in the images.

### C. Feature Selection using Human Group-based Particle Swarm Optimization

In this work, feature selection is done using Human Group-based Particle Swarm Optimization, which has the distinct benefit of simulating human cognitive capacities in optimization problems. By adding a human-guided component, HPSO improves upon the communal intelligence of particle swarm optimization, in which particles stand in for potential subsets of characteristics. The feature selection process is guided by heuristics and important domain experience provided by this human-in-the-loop technique, which increases its efficiency and context awareness. HPSO assures the selection of the most important characteristics while minimizing computational overhead by fusing human understanding with the computational power of PSO. This method is especially well-suited for difficult tasks like satellite image processing where domain knowledge is essential for precise feature selection. It improves the quality of selected

[1]https://ieeexplore.ieee.org/abstract/document/8736785/

characteristics, which in turn improves the efficiency of deep learning models like Convolutional Neural Networks. After generating the characteristic vectors, characteristics are chosen employing the human group-based PSO method. PSO is a population-based searching algorithm that usually simulates bird behaviour. In Eq. (2), is employed to modify the particle's position $p_j$ and velocity $v_j$ in order to produce new locations for each particle.

$$v_j(m+1) = w \times v_j(m) + h_1 \times d_1 \times \left(la_j(m) - p_j(m)\right) + h_2 \times d_2 \times \left(ga_j(m) - p_j(m)\right)$$

$$p_j(m+1) = p_j(m) + v_j(m+1) \quad (2)$$

where, $m$ stands for the number of iterations, $h_1$ and $h_2$ are expressed as random real integers between [0, 1], w is a representation for the acceleration weight, $a_j$ is a symbol for the best position, $la_j(m)$is a symbol for the local best position, and $ga_j(m)$ is a symbol for the global optimal position of the particle. In PSO, an adaptable uniform mutation is used to increase convergence and simplify implementation after the HGO method has been used to initially affect the particles.

A discrete multi-label is first converted into a continuous label using HGO. The employed approach locates the obtained feature vectors in accordance with decision$c_j$, where the vectors of the particle's location are supplied as $p_j(m) = \left(p_j, 1, p_j, 2, p_j, C\right)$.

The feature selection algorithm's capacity for exploration is improved by the adaptive uniform mutation. The variety and choice of the mutation on each particle, $p_j$ in this operator are controlled by a nonlinear function$p_n$. Eq. (3) is used to update $p_n$at each cycle.

$$\mathrm{p_n} = 0.5 \times \mathrm{e}^{\left(-10 \times \frac{\mathrm{m}}{\mathrm{M}}\right)} + 0 \quad (3)$$

Where, m represents the number of iterations, M is designated as the maximum iteration, and the $p_n$value tends to fall as the number of iterations rises. If the $p_n$value is greater than the random number between [0, 1], the mutation selects the s elements at random from the particle. The mutation value of the items contained in the search space is then reset, with s serving as an integer value that limits the mutation range. Eq. (4) mathematically denotes the value of s as:

$$s = max\left\{1, \left|C \times \ p_n\right|\right\} \quad (4)$$

The following describes the human group-based PSO algorithm's step-by-step procedure.

Step 1: Establish the particle swarm's initial parameters, including (a) the number of iterations M, the swarm size $T_k$ , and the archive size $T_b$. A non-dominated solution is saved into the archive after steps (b) initialize the particle locations, (c) estimate the aim of each particle, and do so.

Step 2: The particular best position of the particles is updated using the Pareto dominance relationship. The particular best position of the particles continues to remain unaltered if the new position $p_j(m+1)$ is superior to the previous personal best position$la_j(m)$, set$la_j(m+1) = p_j(m+1)$, where $a_j$ is shown as the best position and $la_j(m)$ is shown as the local best position.

Step 3: Choose the global finest position from the archives according to the variety of solutions. To choose the particle's global optimal position$ga_j(m)$, a binary tournament is employed after initially calculating the crowding distance value.

Step 4: The decision value $c_j$ is then initialized depending on$ga_j(m)$. The feature vector c's decision $c_j$ is each a binary value$c_j = \pm 1, j = 1,2, \dots, T$. Each characteristic vector c is associated to the fitness value V(c), which is thought of as the weighted average of T stochastic contributions$W_i\left(c_i, c_1^i, \dots, c_k^i\right)$. However, the significance of decisions $c_j^i, j = 1,2, \dots, K$ and other K selections affects their contributions.

Eq. (5) mathematically illustrates the fitness function.

$$V(c) \ = \tfrac{1}{T}\textstyle\sum_{i=1}^{T} W_i\left(c_i, c_1^i, c_2^i, \dots, c_k^i\right) \quad (5)$$

The total quantity of variables that interact decision values is denoted by the integer index$K = 0,1,2, \dots T-1$. The parameter$P \in [0,1]$, which represents the probability that each member has been informed of their contribution to the decision, determines the knowledge level of the $n^{th} n^{th}$ member. Each member n determines their individual estimated fitness utilizing (6) depending on their degree of knowledge.

$$V_n(c) = \frac{\sum_{i=1}^{T} \widetilde{c_{ni}} W_i\left(c_i, c_1^i, c_2^i, \dots, c_k^i\right)}{\sum_{i=1}^{T} \widetilde{c_{ni}}} \quad (6)$$

where, $\tilde{c}$ is referred to as the matrix, whose generic member $c_{ni}$ examines the numerical value one with probabilities (P and 0) with probabilities (1-P).

Step 5: Eq. (7) is employed to modify the particle's location $p_j$and velocity $c_j$ in accordance with the decision value$c_j$.

$$v_j(m+1) = w \times v_j(m) + h_1 \times d_1 \times \left(la_j(m) - p_j(m)\right) + h_2 \times d_2 \times \left(ga_j(m) - p_j(m)\right) \quad (7)$$

$$p_j(m+1) = p_j(m) + v_j(m+1) \quad (8)$$

Step 6: Apply Eq. (7) and Eq. (8) to uniform mutation.

Step 7: Utilizing the crowding distance approach, upgrade the external archives.

Step 8: Examine the termination circumstance: if the proposed algorithm completes the maximum number of iterations, the process should be terminated; otherwise, move back to phase 2. The HGO algorithm's fitness function $V_n(c)$ is used to remove the most deficient particles.

### *D. Optimizing CNN Hyperparameters using Ant Colony Optimization Strategy*

The study utilizes Ant Colony Optimization to optimize numerous parameters simultaneously, which makes it a suitable method for fine-tuning Convolutional Neural Network hyperparameters. ACO is an optimization method that draws inspiration from nature and is particularly efficient at navigating intricate search spaces. As such, it may be used to determine the best possible combination of hyperparameters for deep learning models. Its benefit is that it can investigate a large variety of hyperparameter values and adaptively modify them while optimizing. When working with hyperparameters, ACO's probabilistic method is extremely beneficial since it resembles how actual ants choose the shortest path in their natural environment. This method facilitates effective parameter space exploration and exploitation. This work uses the effectiveness of ACO to achieve optimal generalization, decreased overfitting risk, and enhanced CNN performance. As a result, it provides a reliable method for improving the model's accuracy in applications like satellite image categorization. ACO, developed by Marco Dorigo in 1992, is a standard heuristic swarm intelligence program that uses probabilistic calculations to identify the best planning pathway. ACO is a system based on positive feedback in which the ant finally chooses the path with the highest pheromone concentrations in order to obtain the best outcome possible in terms of the regulatory mechanisms.

The Convolutional Neural Network utilized in this study's Deep Learning framework was optimized using ACO. The study also altered the conventional ACO by using multitype ants to simultaneously improve different variables. The total quantity of ant varieties in ACO-DL is equal to the number of characteristics that need to be optimized. As a result, ACO-DL was able to optimize simultaneously a number of parameters related to the model in order to produce the best possible answer to the function of objective. The number of batches (A) in the network and the starting learning rate (L) in Adam were optimized for the CNN framework using ACO. The objective function (F (A, L)) selected was an accurate rate of predictions. Additionally, a given interval's values for A and L were determined in Eq. (9) and Eq. (10).

$$F_{max}(A, L) \tag{9}$$

$$k.t.\begin{cases} A \in [A_{min}, A_{max}] \\ L \in [L_{min}, L_{max}] \end{cases} \tag{10}$$

The fundamental concept is to iteratively discover the shortest path to the best solution of the goal function. In the meantime, the study established the subsequent two termination standards in order to ensure the efficiency of the optimization algorithm: 1) No apparent increase in accuracy; 2) the maximum number of repeats.

*E. Classification Using Convolutional Neural Network*

The CNN is the most efficient and productive approach network among deep learning techniques. Because CNNs can categorize intricate contextual images, they are widely used to categorize remote sensing data. Usually, these methods are not required for completing an output image prediction. CNNs are feed-forward neural structures that employ substantially local correlations to produce judgements by imposing an immediate interaction arrangement between neurons in neighbouring segments of the system. A maximal layer of pooling, the network layer, numerous convolutional layers, and fully linked layers constitute their architecture. Every stage of convolution calculates the weighted average of the prior characteristic using a channel before sending its findings via a stimulation functions to obtain the outcome. Using this method, the kernel measurement is computed to find neighbourhood correlations while preserving consistency for each region throughout the data clusters. The final characteristic pattern is created using constants at the lowest attainable unit level. The many levels of convolutional or layers of pooling are finally interfaced into a coherent unit using a fully coupled network of neurons. Eq. (11) and Eq. (12) gives the convolution operation.

$$fm_n^q(u, v) = UU_{\substack{id(x,y)e_n^q(w,t) \\ d \quad x,y}} \tag{11}$$

$$F_n^q = \left[fm_n^q(1,1), \dots, fm_n^q(u, v), \dots, fm_n^q(U, V)\right] \tag{12}$$

Following the extraction of the characteristics, a down sampling or pooling process is employed to gather the intersection of characteristics that are resistant to moderate transverse changes and deformation. It is given in Eq. (13).

$$R_n^q = s_r\left(F_n^q\right) \tag{13}$$

Similar to this, $R_n^q$ stands for the Qth input feature-map's pooling characteristics-map of the mth layer, and $s_r$ stands for the pooling operation. The maximum, average, L2, overlapping, and spatial pyramid pooling formulae are used in CNN. An activation function is used to speed up learning and offer a method of decision-making for a complicated feature-map. Both the non-linearity of the characteristics and the accelerated learning rate are provided by these activation functions. ReLu, sigmoid, tanh, maxout, and SWISH activation functions all have the same capability for supplying nonlinearity and resolving the vanishing gradient issue.

$$t_n^q = S_x\left(F_n^q\right) \tag{14}$$

$S_x$ stands for the activation function in Eq. (14), $F_n^q$ for the convolution output, and $t_n^q$ for the converted output.

The two main decisions regarding design for CNN that offer superior efficiency and eliminate the overfitting issue are training and optimization. The number of extra problems for training the information generally grows along with the volume of information. The framework has difficulties when a novel or unfamiliar dataset is presented. Overfitting is a result of this issue, which dropout and batch normalization can solve. The dropout mechanism is employed to disable a large number of nodes at the conclusion of each cycle of the training phase. To enhance entire accuracy, strengthen the system's resistance to overfitting, and quicken the gradient descent process' convergence, batch normalization aims to impose a zero mean and a one standard deviation across every activation function in the established layer and for every single inadequate batch. The fully connected layer, the last component of the CNN framework as depicted in Fig. 2, combines every component with an additional layer to categorize. It gathers data from the characteristic extraction phase and analyses the output from every step before it. As a consequence, data categorization is accomplished by nonlinearly linking a set of chosen characteristics.

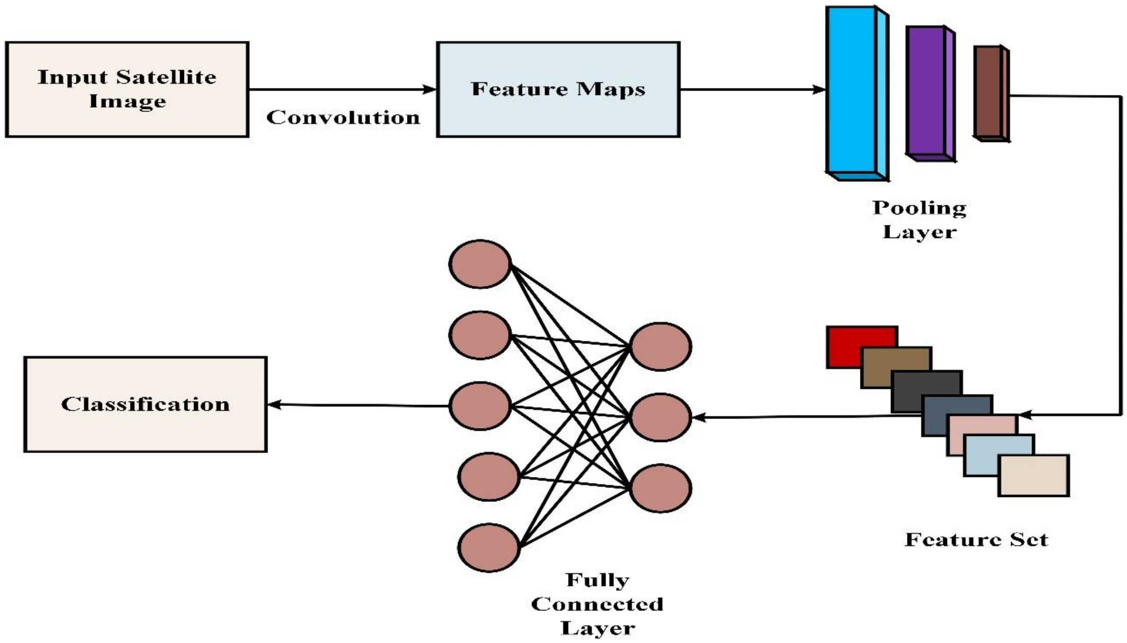


Fig. 2. CNN model.

## V. Results and Discussion

The study first acquired a special EuroSAT dataset made up of twenty-seven thousand annotated satellite images from Sentinel-2 that included thirteen spectral bands and ten different land cover and land use classifications. To improve the quality and usability of these images for subsequent evaluation, necessary pre-processing techniques such as normalization and histogram equalization were used. The main contribution of this research is the combination of CNNs and PSO and ACO optimization approaches to enhance the accuracy of land cover and land use categorization. PSO was utilized to effectively choose the most pertinent spectral bands, decreasing data noise and redundancies. ACO significantly improved crucial CNN hyperparameters including batch size and learning rate, which improved the efficiency of the framework as a whole. On the EuroSAT dataset, the study assessed the hybrid PSO-ACO-CNN architecture and contrasted its performance with that of conventional categorization techniques and independent CNN models.

### *A. Performance Evaluation*

To evaluate the success of categorization, assessment indicators are crucial. The method most frequently used for this objective is an estimation of precision. A classifier's accuracy for any particular set of data may be assessed by the proportion of test datasets that it properly classifies. Because making the optimal decisions will not be possible if the accuracy metric is used alone. To evaluate the performance of the classifier, researchers additionally employed other factors. Accuracy, recall, precision, and F1-score measures were used to evaluate the performance of the suggested technique. The following is a description of each measure's definitions:

$T_{pos}$ (True Positive) refers to the amount of information that has been correctly categorized.

The term $Fpos$ (False Positive) represents the volume of reliable information that was incorrectly categorized.

False negatives ($F_{neg}$) are instances where incorrect information has been given an actual classification.

The categorization of incorrect information values is referred to as $T_{neg}$ (True Negative).

The classifier's accuracy displays how frequently it makes the right assumption. The ratio of accurate forecasts to all other credible hypotheses is known as accuracy. It is demonstrated by Eq. (15).

$$Accuracy = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \tag{15}$$

The amount of correctly classified outcomes is determined by calculating the precision, or level of accuracy, of a classifier. Reduced false positives are the result of improved accuracy, whereas many more are the result of decreased precision. The percentage of instances that are correctly categorized compared to all occurrences is the definition of precision. It is defined by Eq. (16).

$$P = \frac{Tpos}{Tpos+Fpos} \tag{16}$$

The sensitivity of a categorization, or how much relevant information it produces, are determined by recall. The overall quantity of $F_{neg}$ reduces with improved recall. Recall is the ratio of cases that have been correctly categorized to all of the predicted occurrences. This is demonstrable by Eq. (17).

$$R = \frac{Tpos}{Tpos+Fneg} \tag{17}$$

The combination of metrics known as F-measure, which reflects the weighted mean of recall and accuracy, are obtained by adding precision and recall. It is characterised by Eq. (18).

$$F1 - score = \frac{2\times precision \times recall}{precision\times recall} \quad (18)$$

Area under the ROC Curve, or AUC, is a well-known evaluation metric for binary classification problems in deep learning and machine learning. The area under the receiver operating characteristic (ROC) curve, which is a graphic representation of the binary identification algorithm's efficacy, is evaluated by the area under the curve (AOC). The classifier in a binary classified problem tries to figure out whether the input information belongs to a positive or negative division. The $Tpos$ vs. the $F_{pos}$is shown on the ROC curve for various classification criteria. AOC values range from 0 to 1, with higher numbers denoting more efficiency. An absolutely randomized classifier has an AOC of 0.5, whereas an optimal classifier has an AOC of one. Because the method considers all possible degree of detection and provides a single number to compare the performance of different classifiers.

A deep learning model's training and testing accuracy score over a number of training epochs are summarized in Fig. 3. Every row displays the associated training accuracy and testing accuracy for an epoch number that ranges from 10 to 100. Testing accuracy assesses the model's effectiveness on new or validation information, whereas training accuracy shows how effectively the model is effective on the training information it was shown during training. Both training and testing accuracy often increase as the number of training epoch's rises, suggesting that the framework is learning from the information and getting more proficient in generating predictions. The model attains exceptionally accurate levels on both the training and testing datasets by the end of 100 epochs, indicating that it has acquired the ability to generalize to new, unanticipated information successfully. The graph shows the growth of the model's effectiveness as it goes through training.

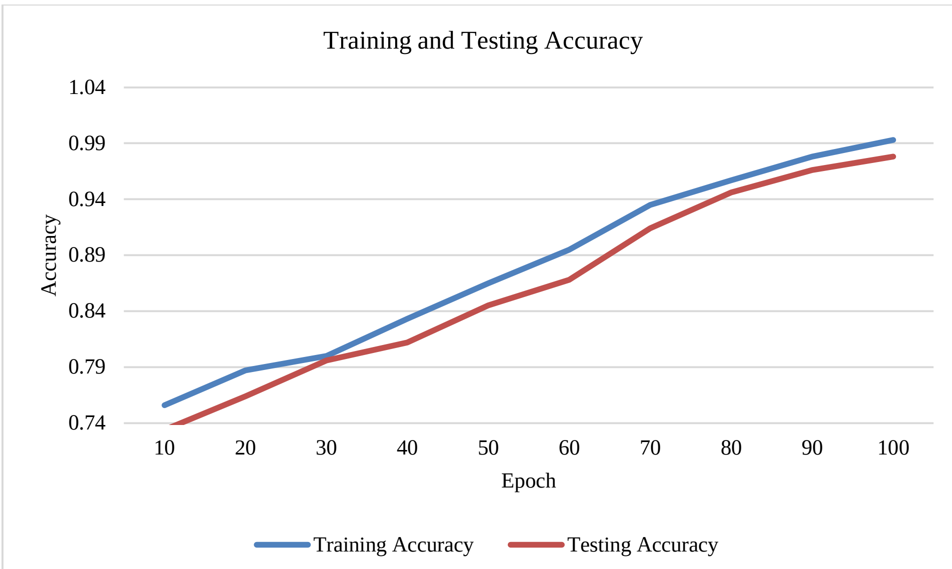


Fig. 3. Training and testing accuracy.

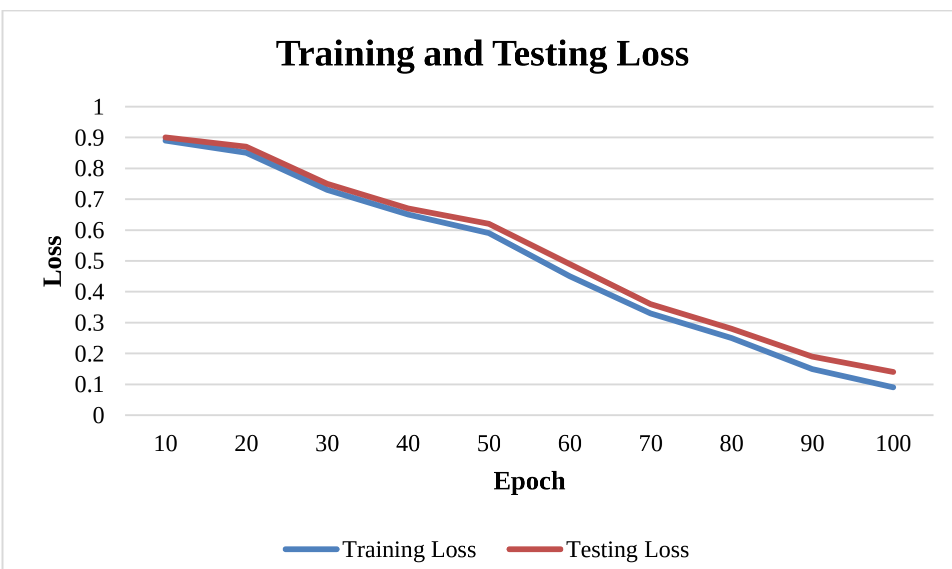


Fig. 4. Training and testing loss.

The testing and training loss values for a deep learning model throughout a variety of training epochs are shown in Fig. 4. The testing loss and the training loss are shown in each row, which is associated with an individual epoch number between 10 and 100. Testing loss evaluates the model's effectiveness on observed or validation information, where usually lower values indicate higher generalization. Training loss examines how well the model fits the training information, with lower values suggesting a better fit. This graph shows that both training and testing loss constantly reduce as the number of training epochs rises. The pattern indicates that if the model is trained, it becomes better at reducing errors and making predictions that are more accurate. The model's decreasing loss values show how it learns, and the lowest losses after 100 iterations show that the model has successfully converged and is capable of making accurate projections on both the training and testing datasets.

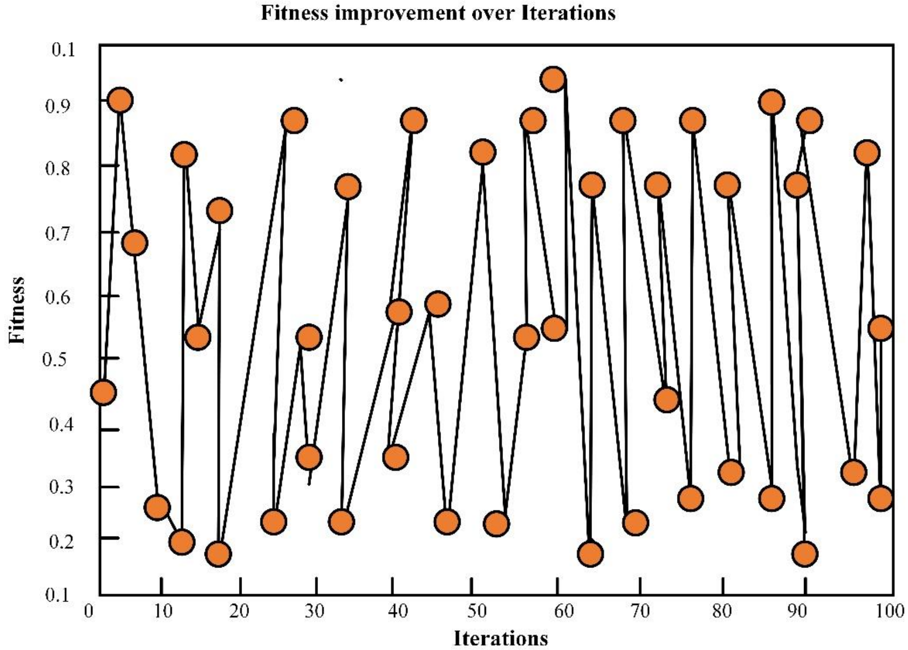


Fig. 5. Fitness improvement over iteration.

The development of an optimization algorithm—specifically, Ant Colony Optimization—over a number of iterations is seen in Fig. 5. The y-axis shows the fitness of the algorithm's created solutions, while the x-axis shows the quantity of iterations or generations. In ACO, fitness often refers to how well or effectively a solution addresses the issue at hand. The algorithm continually updates and improves its solutions to increase their fitness as it moves through iterations. As a result, the graph depicts how the solutions' fitness changes over time and, ideally, converges to an optimum or substantially optimal solution. Any levelling out or stability in the graph's later iterations denotes that the algorithm has probably achieved an optimal solution or a point of decreasing effectiveness. The sharp decrease or large loss in fitness towards the beginning of the graph's iterations signals rapid improvement. This illustration assists in evaluating the algorithm's rate of convergence and potency in locating superior solutions to the current optimization challenge.

The performance metrics of the HPSO-ACO-CNN hybrid deep learning model are summarized in Fig. 6. In order to evaluate the model's performance in a classification position, it offers important assessment metrics. The "Accuracy" statistic measures the model's overall accuracy in making predictions, and a high result of 99.3% shows that the model performs well in terms of categorization. "Recall" (98.7%) assesses the model's capability to properly recognize every single positive example, while "Precision" (99.2%) measures the model's capacity to correctly categorize positive cases. Precision and recall are combined into one score called the "F1-Score" (98.7%), which takes into account the trade-off between both. The HPSO-ACO-CNN model is very accurate and dependable in its categorization task, with an especially strong capacity to categorize positive situations properly while retaining a high overall accuracy level, according to these high values across all metrics.

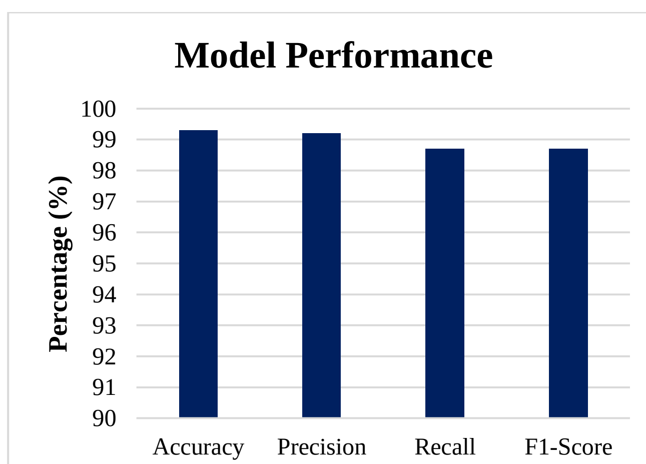


Fig. 6. Model performance.

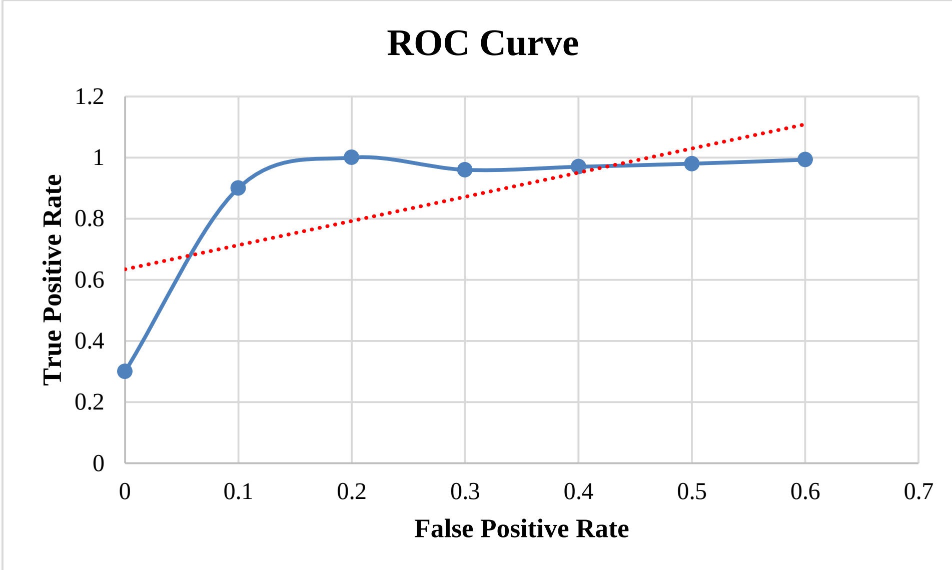


Fig. 7. ROC curve.

The True Positive Rate and False Positive Rate values for a binary categorization model at various threshold levels are shown in Fig. 7. These numbers are frequently employed to build a ROC curve. The fraction of real positive cases that the model properly classifies as positive is measured by TPR, sometimes referred to as sensitivity or recall.

TABLE I. COMPARISON OF PERFORMANCE METRICS OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

| Models | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| DNN [25] | 88.2 | 87.89 | 90 | 90 |
| MSVM [26] | 93.70 | 94.90 | 96.50 | 94.90 |
| LSTM [27] | 97.40 | 97.80 | 98.70 | 97.80 |
| Proposed HPSO-ACO-CNN | 99.3 | 99.2 | 98.7 | 98.7 |

On the other hand, FPR measures the percentage of real negative cases that the model misclassifies as positive. The graph displays how these rates alter when the threshold for categorization changes from 0 to 0.6. The TPR typically rises as the threshold rises, showing that the model gets better at properly recognizing positive situations but frequently at the expense of a larger FPR. The ROC curve, created from these results, graphically illustrates the trade-off between TPR and FPR at various threshold levels, assisting in evaluating the model's categorization effectiveness and determining the best threshold in accordance with the demands of the particular application.

The suggested HPSO-ACO-CNN is a hybrid of the Deep Neural Network (DNN), Multiclass Support Vector Machine (MSVM), Long Short-Term Memory (LSTM), and Deep Neural Network for a specific task. The Table I and Fig. 8 provides a number of significant efficiency measures for each model, one for each row: "Precision" measures the model's capacity to accurately classify positive cases, "Recall" measures the model's capacity for correctly recognizing all actual positive cases, and "F1-Score" is a balanced metric combining precision and recall. "Accuracy" denotes the overall proportion of correct predictions generated by the model.

The outcomes show that the suggested HPSO-ACO-CNN model exceeds the competition with the greatest values for accuracy (99.3%), precision (99.2%), and F1-Score (98.7%), demonstrating its better performance in the task at hand. Additionally, LSTM performs well, whereas DNN and MSVM score slightly more severe on these criteria. Together, these measures offer insightful comparisons of these models' success in the particular categorization task, with higher values representing better model effectiveness.

TABLE II. COMPARISON OF DATASETS OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

| Datasets | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Landsat 8 Imagery 2014 [28] | 89 | 87 | 87 | 88 |
| Landsat 5 Thematic Mapper Imagery [29] | 94.17 | 95 | 96 | 94 |
| Proposed EuroSAT Dataset | 99.3 | 99.2 | 98.7 | 98.7 |

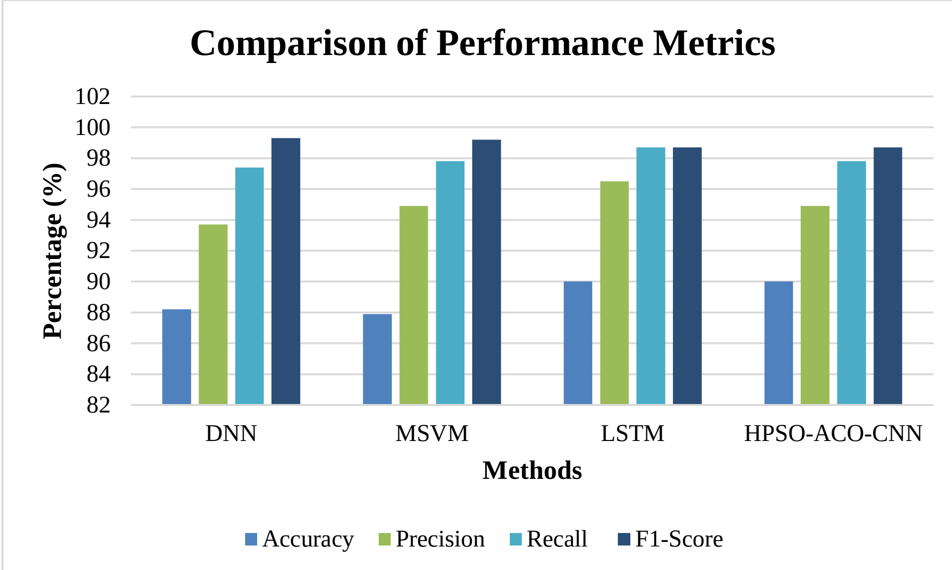


Fig. 8. Comparison of performance metrics of proposed method with other existing approaches.

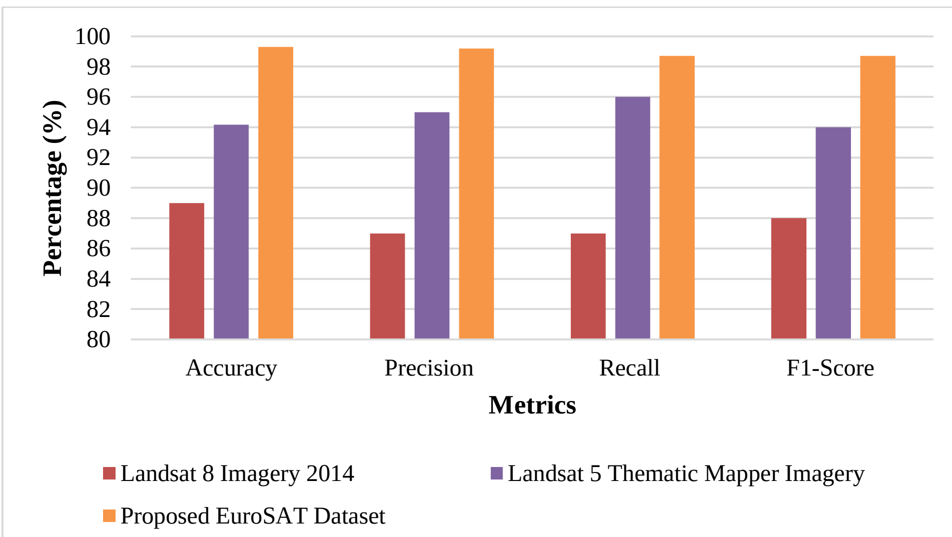


Fig. 9. Comparison of datasets of proposed method with other existing approaches.

A comparison of datasets utilizing the suggested approach in comparison to other current methodologies is shown in Table II and Fig. 9. Four important criteria are used to assess their effectiveness: F1-Score, Accuracy, Precision, and Recall. The initial dataset, the 2014 Landsat 8 Imagery, has an accuracy of 89%, 87% recall, 87% precision, and an 88% F1-Score. Landsat 5 Thematic Mapper Imagery, the second dataset, was particularly better than the initial one, with an F1-Score of 94%, accuracy of 94.17%, precision of 95%, and recall of 96%. The suggested EuroSAT Dataset performed outstandingly, achieving 98.7% recall, 99.2% precision, 99.3% accuracy, and a 98.7% F1-Score. These findings show that the suggested EuroSAT Dataset outperforms the other datasets in all four standards, indicating that it is the most effective alternative for the given objective, which is probably connected to the categorization or analysis of satellite images. Variability in data features, including resolution, spectral bands, and landscape variety, might be the cause of the variances in comparison results between datasets. The suggested methods could perform better on datasets whose properties are comparable to those that were encountered during the development of the EuroSAT dataset. These datasets might include high-resolution and diversified satellite images.

### *B. Discussion*

The findings show that the proposed HPSO-ACO-CNN model has a number of benefits over other machine learning techniques already in utilization for the categorization of land use and land cover using satellite images. With an accuracy of 99.3%, precision of 99.2%, recall of 98.7%, and an F1-Score of 98.7%, the HPSO-ACO-CNN model outperformed in all assessment measures. These findings demonstrate that the hybrid technique, which combines a CNN with PSO and ACO, significantly improves the classification capabilities of the model. The model excels at accurately detecting positive instances while reducing false positives and false negatives, as seen by its excellent accuracy and recall scores. A precise categorization of land cover and land use is essential in applications like environmental monitoring and catastrophe management. While DNN and MSVM are reasonable models in comparison, they fall short of HPSO-ACO-CNN's performance. Although the LSTM model also exhibits comparable performance, HPSO-ACO-CNN stands out because to its greater accuracy and precision. These results illustrate the effectiveness of combining deep learning methods with optimization algorithms, emphasizing the potential for more precise and reliable mapping of land use and land cover in the context of sustainable land management and protecting the environment.

## VI. Conclusion and Future Works

The study concludes by presenting a novel technique that substantially enhances the precision of classifying land use and land cover using satellite images. The merging of ACO, CNN, and HPSO algorithms results in significant performance increases in the proposed HPSO-ACO-CNN model. Combining CNN hyperparameter optimization with spectral band selection yields remarkable accuracy, precision, recall, and F1-Score performance for this hybrid architecture. Results from experiments conducted on the EuroSAT dataset demonstrate how well the HPSO-ACO-CNN model performs when compared to other methods and standalone CNN models. In addition to addressing important problems with feature selection, parameter optimization, and model training, the work creates new opportunities for satellite image analysis. This novel method has great potential for a number of uses, such as sustainable land use, urban planning, environmental monitoring, and disaster management. It highlights how deep learning techniques and optimization strategies may be combined to improve remote sensing applications. Regarding potential avenues for future research, there are a number of intriguing options to consider. An intriguing line of investigation is the expansion of the HPSO-ACO-CNN architecture to handle larger and more complicated datasets of satellite images, potentially incorporating other spectral bands and land cover categories. Additionally, assessing the model's resilience and scalability in various environmental conditions and geographical areas may yield unexpected findings. Finally, there is potential to further the more general goals of environmental conservation and sustainable land management by investigating applications of transfer learning and customizing the model for additional Earth observation tasks, such change detection and crop monitoring.

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