Enhancing Optical Sensor Image Classification through Deep Learning with Convolutional Neural Network

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Abstract: Applications for satellite images are numerous and include environmental surveillance, security, and disaster recovery. Identifying infrastructure and entities in the images by hand is necessary for these applications. Automation is necessary since there are numerous regions to be addressed and a limited number of specialists accessible for performing the searches. However, the issue cannot be resolved by conventional object recognition and categorization techniques since they are too erroneous and unstable. A set of machine learning techniques called deep learning has demonstrated potential for automating these kinds of operations. Through the use of convolutional neural networks, it proved effective at comprehending images. This paper investigates how deep learning can be used to improve the categorization of optical sensor images, with an emphasis on Convolutional Neural Network (CNN). Optical sensor pictures provide insightful information for a variety of uses, including precision farming, tracking the environment, and analysis of land cover. Consequently, to enable more precise and effective categorization, this research makes use of CNN ability to automatically develop hierarchical representations. The effectiveness of deep learning within this field is demonstrated by comparing the model's performance versus conventional classification techniques. The results of this study add to the expanding amount of research in remote sensing utilizing image analysis by offering a solid framework for enhancing the precision and effectiveness of optical sensor picture categorization by utilizing CNN and innovative deep-learning methods. MATLAB is used to implement the suggested framework. The suggested approach outperformed region-based GeneSIS, OBIA, segmentation and classification tree method, fuzzy C means, and segmentation with an accuracy of 95%.

1 INTRODUCTION

Optical sensor images are essential to modern remote sensing because they collect visible and near-infrared wavelengths, providing a unique view of the Earth's surface. Sensors like this are essential parts of satellites as well as other aerial platforms, offering a large amount of data for a wide range of uses, such as agricultural management, environmental surveillance, hazard review, and land use classification. Optical sensors work fundamentally by identifying and capturing sunlight scattered off the surface of the Earth. Different surface characteristics may be distinguished due to the sensors' numerous spectral bands, which each catch light at a distinct wavelength (C. Li et al., 2019). In addition to the near-infrared, which can be especially useful for vegetative study, typical spectral categories include the red, green, and blue bands. High spatial resolution optical sensor pictures deliver comprehensive images of the surface of the Earth, which is one of their main advantages.

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This quality is critical for activities where precise decision-making depends on tiny details, like precision farming, urban design, and tracking infrastructure. Optical sensor images greatly enhance environmental surveillance. These sensors can track urbanization, recognize deforestation, identify variations in land cover, and evaluate ecosystem health. Moreover, optical pictures play a crucial role in the research of natural catastrophes, supporting the evaluation of the damage resulting from crises like earthquakes, floods, as well as wildfires (B. Rasti and P. Chamise 2020)

Optical sensor pictures help with precision farming in agriculture by revealing information about the health of crops and the vitality of plant life. Farmers can enhance water supply, by applying fertilizers, and insect management by being able to discern among affected and healthy vegetation due to the distinct spectrum. This accuracy supports sustainable farming methods and higher crop yields. Optical sensor image incorporation with geographic information systems (GIS) makes it easier to create precise and comprehensive maps. Optical imagery-derived maps of land use and vegetation are important tools for managing resources, urban development, and preservation of the environment. A fundamental component of remote sensing, optical sensor images provide for a thorough comprehension of the motions in the Earth's surface (Y. Bazi et al., 2021). They have a wide range of uses and offer vital data for disaster, farming, and environmental control. The combination of sophisticated analytical methods like deep learning with optical sensor imaging has an opportunity to significantly improve the capacity to observe and understand the complexity of this developing planet as technology develops.

A vital component of remote sensing as well as geospatial analysis is the classification of optical sensor images, which uses innovative methods to analyse and classify data gathered from optical sensor imaging. Through this method, different areas or pixels inside a picture are assigned specific groups or signs, enabling a detailed comprehension of the exterior of the Earth and its changing aspects. The fundamental goal in optical sensor image categorization is to automatically extract useful data from enormous data sets so that it may be used for effective evaluation and selection in a variety of fields. Applications including land cover visualization, agriculture, urban development, environmental monitoring, and disaster response fall under this category. Advanced categorization algorithms transform optical sensor images into indispensable instruments for deriving meaningful conclusions from detailed visual data (M. P. Uddin et al., 2021). The initial phase in the categorization process is obtaining excellent quality optical sensor imagery, which is usually obtained using satellites or aerial platforms. There are several spectral bands in these pictures, and each one corresponds to a distinct light wavelength. Typical bands that together give a complete picture of the Earth's surface are red, green, and blue, along with near-infrared. Categorization is based on the unique spectral fingerprints of different features, including flora, water, cities, and bare soil. Usually obtained by satellites or aerial platforms, the categorization process starts with the collection of detailed optical sensor imagery. Several spectral bands, each denoting a distinct light wavelength, are seen in these pictures. Red, green, blue, as well as near-infrared are common bands that together offer a complete picture of the surface of the earth. Categorization is based on the different spectral signatures of different characteristics, including bare soil, vegetation, water, and urban surroundings (F. Zhou and Y. Chai et al., 2020).

The two main methods used in visual sensor classification of images are supervised as well as unsupervised classification. A machine learning algorithm is developed utilizing labelled samples, wherever each pixel in the image is connected with an identified class, in supervised classification. The remaining pixels are subsequently classified using machine learning methods, such as random forests, neural networks, and support vector machines, among others, by the patterns that were previously learned (X. Lei, H. Pan, and X. Huang et al., 2019). In contrast, unsupervised classification entails clustering pixels without the need for pre-established classifications. To find patterns and groups, this approach depends on the data's intrinsic statistical characteristics. In unsupervised classification, clustering algorithms like k-means as well as hierarchical clustering are frequently utilized. Optical sensor image categorization has several issues, such as managing environmental conditions, spectral fluctuation, and mixed pixels a pixel that combines information from several types of land cover. Processing techniques like atmospheric and radiometric adjustments are frequently used to lessen these difficulties and improve the precision of the categorization findings. The inclusion of deep learning methods, in particular, Convolutional Neural Networks has greatly improved the categorization of optical sensor images. To capture complex patterns including spatial connections, CNNs are particularly good at developing hierarchical features from images. Deep learning-based classification techniques become even more accurate and efficient via transfer learning, in which trained models are adjusted for particular classification tasks (S. Bera and V. K. Shrivastava 2020).

More and more high-resolution optical sensor footage is becoming available, opening up previously unheard-of possibilities for monitoring the environment, land cover mapping, and earth observations. The abundance of data obtained by optical sensors offers a valuable resource for resource management and knowledge on planet. However, the real use of this imagery depends on precise and successful classification algorithms that can identify intricate patterns and characteristics in the data. The fine features present in high-resolution optical sensor images frequently make conventional image categorization techniques ineffective. This work sets out to improve optical sensor image classification by employing deep learning, with a particular emphasis on CNNs, as a solution to these difficulties (L. Khelifi and M. Mignotte 2020). In the field of image analysis, deep learning has become a game-changing paradigm that has shown amazing promise across a range of applications, including computer vision, healthcare imaging, and remote sensing. An especially good subclass of deep learning algorithms for autonomously extracting structured representations from picture data is CNNs. They are particularly well-suited for jobs like optical sensor image classification, where minute details are essential for precise interpretation, because of their capacity to record complex spatial data. The realization that using CNNs to their full potential will greatly increase the precision and effectiveness of optical sensor image classification is what spurred this research. Customized feature extraction, which is typical in traditional picture classification algorithms, has limitations. Deep learning mitigates these limitations by enabling the algorithm to learn its own useful features from the data (Y. Feng et al., 2019).

The pre-processing of optical sensor data is the first step in the extensive pipeline that makes up the methodology used in this work. The model is trained with normalization and augmentation techniques to improve its ability to generalize patterns in a variety of settings and conditions. Afterward, a meticulously selected dataset is utilized for both assessment and training, guaranteeing that the model is exposed to a typical portion of optical sensor imagery (D. Hong et al., 2020). The proposed methodology is based on the creation of a CNN framework specifically engineered for the classification of images from optical sensors. Because the CNN is set up to extract features hierarchically, the model can identify global as well as local trends in the picture. Thorough experimentation is used to validate the architecture's efficacy and recognized measures like accuracy, precision, recall, and F1-score are used to assess the model's performance. This study investigates the possibilities of transfer learning as well as fine-tuning approaches, going beyond the traditional bounds of deep learning. The research focuses in particular on the use of the ResNet50 design, a deep neural network that has already been trained, for optical sensor image classification. Transfer learning is a technique that improves performance on one job (like image recognition) by utilizing knowledge from another related task (like optical sensor image classification). The model that was previously trained is further improved by fine-tuning so that it can conform to the unique subtleties of the optical sensor images. In brief, this study attempts to advance the development of methods for classifying optical sensor images by utilizing CNN's powers inside a structure for deep learning. The ensuing sections of this research will examine the comprehensive technique, experimental outcomes, and conversations that jointly mould the comprehension of the possibilities and obstacles linked with this innovative strategy. The following are the main contributions:

- CNNs are utilized to automatically extract hierarchical characteristics from optical sensor images, thereby capturing complicated patterns and spatial correlations for improved classification accuracy.
- By combining deep learning techniques with CNNs, the model's capacity to generalize patterns over many scenarios and environments is improved, leading to better classification results on unknown data in a variety of environmental contexts.
- This method, which uses CNNs, lessens the dependence on features that are manually generated, enabling the model to independently learn and adjust to the distinctive qualities seen in optical sensor pictures.
- CNNs are particularly good at analysing high-resolution optical sensor pictures because they can handle the extensive details included in the data and offer a solid foundation for accurate land cover classification.
- By utilizing information from larger image data sets, transfer learning techniques more specifically, fine-tuning pre-trained CNN models help to increase classification precision and effectiveness in optical sensor image processing.

To allow for an organized investigation of the subject, this work is divided into multiple important sections. Section 1 provides background details and explains how and why using CNNs in conjunction with deep learning can enhance the classification of optical sensor images. Section 2 outlines the procedures for initial processing, preparing the data, and CNN structure in addition to the related works approach. Section 3 describes the limitations of the current system. In Section 4, the suggested framework methodology is explained. Section 5 presents the experimental results and evaluates the model's performance using standard metrics. Section 6, which provides guidance for future research and highlights significant findings, serves as the work's final section.

2 RELATED WORKS

Deep learning-based techniques for classifying hyperspectral images (HSI) have advanced significantly in the last few years. The accuracy of classification is significantly enhanced by these data-driven approaches' improved feature extraction capabilities. Nevertheless, to achieve the ability to extract features adaptable for the target picture when confronted with a fresh HSI for classification, the prior methods typically necessitate retraining the networks from the start, which is a laborious and repetitive procedure. Sun et al. 2022. Think about delaying this procedure and using pre-training to give the network strong feature extraction and generalization capabilities. As a result, without the need for retraining, the network allows for the immediate extraction of specific HSI properties. In order to do this, they reconsider the 3-D HSI data collected from the standpoint of spectroscopic sequence and make an effort to extract information about spectral variations as the spectrum's movement characteristic. Then, to learn the information about detecting spectral variations, they build an unsupervised spectrum movement feature learning structure (SMF-UL) that can be trained on bulk unstructured HSI data. Additionally, create an expandable training dataset to accomplish the enlargement of the original information for initial training. A construction approach that may efficiently use the constantly expanding bulk of unlabelled HSI data by integrating sensors, bands, and HSIs of various sizes into a single training set. Lastly, to prevent the tedious process of retraining the network, they employ the network that was trained to immediately gather the spectrum of motion characteristic of the desired HSI for classification. Numerous tests demonstrate that the suggested SMF-UL gains the reliable ability to extract features with generalization through unsupervised training on large amounts of unlabelled HSI data. Additionally, the obtained spectrum motion feature's accuracy in classification is comparable to sophisticated in-domain and cross-domain techniques, demonstrating its flexibility and supremacy.

Xu *et al.*,2019 presents the scientific results of the IEEE Geophysical and Remote Sensing (RS) Society's Image Processing and Data Fusing Technical Committee's 2018 Data Fusion Contest. Using sophisticated multi-source optical remote sensing techniques (multispectral LiDAR, hyperspectral photographic imaging, and very excellent quality imagery), the 2018 Competition tackled the topic of urban surveillance and supervision. The goal of the competition was to differentiate between a wide range of intricate classifications of urban items, materials, and vegetation based on the classification of the use of urban land and land cover. In addition to merging data, it measured the individual strengths of the new sensors that were employed to get the information. To maximise the amount of data accessible, participants suggested complex strategies based on machine learning, computer vision, and remote sensing. It's also important to note that post-processing and ad hoc classifiers were crucial in both winner records, contributing to a 15% improvement in total accuracy. Even though decision fusion techniques were previously presented in this study, there is still more work to be completed, particularly in terms of automatically integrating and fusing expert information into NNs. Furthermore, this kind of knowledge typically makes sense for all individuals and supports the choice. It will be lucrative to do more study to make CNN more understandable to aid in the public's acceptance and spread of these techniques. In terms of the information, multi-spectral LiDAR by itself and even the fusion of various sources was shown to be very insightful, as these sensors yielded the best LULC categories (accuracies of over 80% in general and 71% on average). Additionally, rasterized 2.5D was the sole method used to handle LiDAR data. This points to possible directions for creating methods that can analyse and categorize actual 3-D sensor data. The data was re-released after the competition and will continue to be freely accessible for the society's advantage. All relevant material is available on the IEEE GRSS site for anyone interested. The training data with matching labels or the test information can be downloaded after enrolling on the IEEE GRSS DASE server. The classification outcomes can then be submitted to receive efficiency statistics, compared with other customers, and, ideally, improve upon the results reported in this work. Because it is the biggest accessible HS dataset having ten times more labelled data compared to the popular Salinas or Pavia datasets or the initial multispectral-LiDAR dataset, we do think it could have a significant influence on the integration of data study as well as the growth of single-sensor handling.

Li *et al.*,2019 explains that the classification of ground objects paired with multivariable optical sensors is an important subject at the moment because of the advent of high-resolution optical sensors. Convolutional neural networks and other deep learning techniques are used for feature extraction and categorization. This paper proposes a unique hyperspectral image classification technique using deep belief networks (DBNs) stacked by limited Boltzmann machines and multimodal optical sensors. To categorize spatially hyperspectral data collected by sensors using DBN. Subsequently, the enhanced approach which combined spectral and geographical data was confirmed. The DBN model was able to acquire features after supervision fine-tuning and uncontrolled pre training. They also included logistic regression layers so that the hyperspectral photos could be categorized. Additionally, tests were conducted using the Indian Pines and Pavia Universities dataset to evaluate the suggested training strategy, which combines spectral and spatial data. The following are the benefits of this approach over conventional methods: Tests show that the method beats other deep learning algorithms and conventional classification. (1) The neural network has a complex structure and a higher ability to gather features than conventional classifiers. Features impact the final model's performance and serve as its training information. In theory, a deep neural network (DNN) could gather more information and learn more complicated functions if it has additional concealed layers. Consequently, a detailed description of the DNN model is possible. Based on the DBN approach, this paper suggests a novel approach to hyperspectral picture classification. Pre training, modification, and data pre-processing are all part of the fundamental DBN classification paradigm. The incorporation of pre training distinguishes DBN from a neural network. In the DBN model, the starting weight value may be rather near to the global optimization. Consequently, the accuracy of the greedy layer-wise supervision learning is higher than that of a neural network. The mini-batch DBN model verifies the learned characteristics and the loss functions to update the weights w during the supervised fine-tuning process. During every training period, variables are taught in mini-batches.

Popowicz and Farah 2020, explores the complex field of dark current, which is a crucial component that affects the appearance of scientific photographs that are obtained using charge-coupled devices (CCDs). Impulsive noise in pictures is frequently caused by dark current, which is a result of faults and contaminants in the fabrication process. Its stability has historically been associated with temperature. But the study also reveals a unique feature of dark currents in proton-irradiated detectors: a range of metastable phases that present formidable obstacles to picture correction. Using Kodak KAI 11000M CCD sensors, which were used for seven years of in-orbit operations during the BRITE (Brightest Target Explorer) astrophysics mission, the study covers a hitherto unheard-of temporal range, wide temperature changes, and a large number of examined pixels. An essential tool for locating and describing these metastable phases in the dark current is a specialized methodology based on the Gaussian mixture model. The results give a sophisticated understanding of the features of the Meta stabilities linked to dark current and provide significant fresh insights into how they operate. The study provides new insights into the difficulties of modelling and controlling dark currents in image sensors used in a challenging space environment. Specifically, the study reveals experimental laws guiding the behaviour of darkness current in tri stable faults. This provides a thorough examination, opening the door to better methods for calibrating and enhancing the performance of image sensors, especially in the setting of astrophysics expeditions where accurate and trustworthy image data is crucial. This study addresses important features of image sensor operation in space applications, and its long duration and thorough investigation of dark current features make it a substantial contribution to the area.

Labelling land use/land cover (LULC) gathered by several sensors with varying spectral, geographical, and temporal resolution is facilitated by the use of remote sensing data. For the investigation of LULC change and modelling in hazy mountain regions, the combination of an optical image with a synthetic apertures radar (SAR) image is important. Zhang *et al.* 2020 proposes a unique feature-level fusion framework, wherein LULC classification experiments are carried out using a fully polarised Advanced Land Observing Satellite-2 (ALOS-2) picture and Landsat operational land imager (OLI) images that have different cloud coverings. They use the Karst Mountains in Chengdu as study region. After that, they extract the characteristics from the optical and SAR pictures' spectrum, texture, and space, correspondingly. They also add additional pertinent data, such as altitude, slope, and the normalized difference vegetation index (NDVI). Moreover, object-oriented multi-scale segmentation is applied to the fusion features image, and the study is then carried out using an enhanced SVM models. The outcomes demonstrated the benefits of the suggested framework, which include high classification efficiency, data from multiple sources, a combination of features, and use in mountainous regions. Overall accuracy (OA) was over 85%, and the values of the Kappa coefficient were 0.845. When it came to artificial surfaces, lakes, gardens, and forests, the fusion image's accuracy was greater than that of a single source of information. Furthermore, there is a relative benefit in the collection of water, artificial surfaces, and shrub land using ALOS-2 data. The purpose of this study is to serve as a guide for choosing appropriate data and techniques for LULC categorization in misty mountain regions. In overcast mountainous regions, the fusion characteristics of the pictures should be prioritized; in less cloudy periods, Landsat OLI data must be chosen; and in situations where data from optical remote sensing are unavailable, fully polarised ALOS-2 data are a suitable stand-in.

In general, this collection of research papers covers a broad range of topics in the field of remote sensing and highlights advancements in classification methods and applications. To create strong extracting feature capabilities without requiring a lot of retraining, a method for unattended spectrum motion learning of features in hyperspectral image classification. An enhanced multi-sensor optical imaging for urbanized land cover and land use categorization is discussed along with the results of the 2018 IEEE GRSS Information Fusion Competition. It emphasizes how different optical sensors can be integrated and how convolutional neural networks function well for addressing intricate and varied urban classes. The benefits of deep learning over conventional techniques for feature extraction and classification, proposing a deep belief network methodology for spectral-spatial grouping of hyperspectral distant sensor data. The metastable dark currents in BRITE Nano-satellite imaging sensors provides a thorough examination of the metastable in nature states in charge-coupled electronics and their consequences for astrophysics missions' image calibrating. To enhance classification performance via multi-source data integration, an innovative feature-level fusion framework for classifying land use and land cover in overcast mountainous locations using optically and SAR sensor pictures. Nevertheless, these studies have certain drawbacks, such as the requirement for large labelled datasets, the influence of metastable dark currents on image resolution in space-based detectors, and possible difficulties in interpreting the models for deep learning techniques (B, Selvalakshmi, Hemalatha K, et al. 2025). Additional investigation could potentially tackle these constraints and improve the usefulness of the suggested approaches.

3 PROBLEM STATEMENT

The current optical sensor image classification algorithms have several drawbacks, including the use of handmade characteristics that may not be able to adequately capture the complex patterns found in high-resolution imaging. The intricacy and unpredictability of optical sensor information can pose challenges to traditional approaches, particularly in situations where there are a variety of land cover types (L. Ding, H. Tang, and L. Bruzzone 2020). Significant obstacles also include the requirement for laborious manual tagging and the difficulty of generalizing to previously unseen data. However, there are strong benefits to using CNN and deep learning for optical sensor picture classification. The model is able to identify intricate spatial connections and trends within optical sensor pictures thanks to the use of deep learning with CNNs that enables automated (P, Elayaraja et al., 2024) and hierarchy extraction of features. By enhancing the algorithm's flexibility to various scenarios and drastically reducing reliance on manually created features, this technology eventually improves classification effectiveness and precision. Additionally, the application of CNNs facilitates transfer learning by enabling the algorithm to be customised for particular optical sensor datasets and take advantage of information from pre-trained networks, hence resolving the issues related to the requirement for huge labelled datasets. In general, the deep learning-based method improves optical sensor image classification's durability, accuracy, and generalization capabilities, which makes it an exciting advance for remote sensing uses.

4 OPTICAL SENSOR IMAGE CLASSIFICATION THROUGH DEEP LEARNING WITH CONVOLUTIONAL NEURAL NETWORK

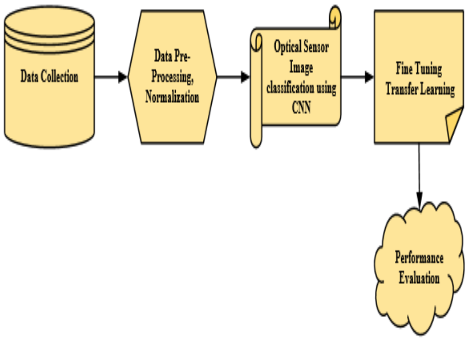

Figure 1: Architecture diagram of proposed CNN transfer learning model.

Several crucial phases are included in the process for improving the optical sensor classification of images using deep learning with CNNs. Initially, pre-processing is applied to the optical sensor imagery, including activities like normalization to improve a model's generalisation across various settings and conditions. After that, a large dataset is carefully selected to guarantee that a variety of optical sensor images are represented for training and assessment. Next, the convolutional and pooling phases of the CNN architecture are set up and tailored to support the hierarchical extraction of features, thereby preserving spatial patterns and correlations. During the training stage, backpropagation and optimization methods are used to adjust the CNN's weights using the carefully selected dataset. By using CNN models that have been trained on extensive image datasets, transfer learning is investigated to improve the model's ability to extract features. Validation datasets are used, and hyper parameters are adjusted, to reduce excessive fitting. After training, the CNN is used to classify previously unknown optical sensor images, and its efficacy is carefully assessed using common metrics such as accuracy, precision, recall, and F1-score. The whole approach seeks to improve the precision and effectiveness of land cover categorization by utilizing deep learning to learn on its own and retrieve characteristics from optical sensor data.

Figure 1 illustrates the methodical procedure that deep learning using CNNs uses to improve optical sensor image classification. To improve the model's resilience, raw optical sensor pictures are first pre-processed and then normalized and enhanced. Then, appropriate samples for training and evaluation are included in a diversified dataset. Convolutional and pooling layers are included in the design of CNN to enable hierarchical feature extraction. To maximize the model's adaptation to optical sensor input, transfer learning is used by initializing the framework with weights that have been trained. During the training stage, the CNN is fed the carefully selected dataset, and optimization and backpropagation methods are used to adjust the model's parameters. In order to avoid overfitting, validation data sets are useful for hyper parameter tweaking. Following training, unknown optical sensor image classification is carried out by CNN, and standard metrics are employed to thoroughly assess the accuracy of the model. By utilizing the capabilities of deep learning, this method greatly increases the precision and effectiveness of land cover categorization by enabling CNN to independently learn complicated characteristics from optical sensor data.

4.1 Data Collection

The suggested feature-selection strategy is evaluated using the RSSCN7.2 sensor scenario data set (Z. Zhao et al., 2020). Sensor images from three distinct groups make up the data collection RSSCN7. The datasets have been designated as follows: Water, Land, and Forest. A total of 400 images were gathered from Google Earth for every group; these images have been selected on four distinct scales, with 100 images for every level. Every picture is 400 x 400 pixels in size. Because of the extensive variety of scene photos that are collected on various scales and taken in a range of weather conditions and seasons, this gathering of information presents certain difficulties. There is a set of training as well as validation data sets built for every optical sensor image.

4.2 Data Pre-Processing

To standardize the size of input characteristics and guarantee consistent and accurate model training, data normalization is a crucial pre-processing technique that is frequently used in machine learning as well as deep learning. The principal aim is to convert numerical information into a uniform range, mitigating the effects of disparate scales and fostering convergence in the training stage. Data normalization in the setting of optical sensor image classification with CNNs entails modifying the picture pixel values. Scaling the value of pixels to a conventional range, like [0, 1] or [-1, 1], is a popular method. This is commonly accomplished by deducting the average pixel intensity value and dividing the result by the standard deviation. Normalization prevents some characteristics from predominating because of disparities in magnitude by ensuring every feature (pixel) serves proportionately to the model's learning process. This procedure improves the model's capacity to identify correlations and trends in the optical sensor visuals, which in turn improves classification accuracy and generalization. It also helps the system converge more quickly throughout training.

A statistical method called data normalization is used for scaling and centring a feature's measurements to ensure they lie in a predetermined range. Normalization is carried out to the picture values of pixels in the setting of classifying optical sensor images using CNNs. The typical normalization formula is shown in eqn. (1):

$$N = \frac{j-E}{SD} \tag{1}$$

Where E is the data sets mean, SD is the Standard Deviation, and j is the variable's starting value. Deviation Z is the standardized value.

The data is scaled to have a variance of one and is centred on zero throughout the normalization procedure. By ensuring that the characteristics have comparable scales, this change stops some features from controlling the learning process because of disparities in size. For deep learning algorithms, such as CNNs, to be trained effectively, optimization methods, such as that of gradient descent, must converge. Normalization helps the model perform better and converge more quickly on optical sensor imagery, which improves model generalization.

4.3 Convolutional Neural Network

A CNN is a particular kind of deep neural network that is used to handle data that resembles a grid, including frames from videos and photos. In the field of optical sensor image classification, CNNs are essential because they offer a strong framework for identifying complicated patterns and characteristics in the images. CNNs use convolutional layers in optical sensor classification to identify unique visual features like edges, colours, and spatial patterns. Activation functions for adding non-linearity, such as Rectified Linear Unit (ReLU), pooling layers for spatial down sampling, and fully linked layers for the highest-level feature integration, come after these layers. The CNN architecture is especially appropriate to the subtleties of optical sensor data because it makes it possible for structured representations to be automatically learned. This is key for distinguishing minute details that are important for classifying land cover and land use. Moreover, transfer learning in which CNNs use models that have been trained on massive image datasets works well in situations where there is a dearth of labelled optical sensor data because it enables the model to adjust and perform well in particular optical sensor tasks such as classification. In addition to improving classification accuracy, the combination of CNNs and optical sensor data offers a strong basis for deriving significant insights from a variety of dynamical optical sensor pictures.

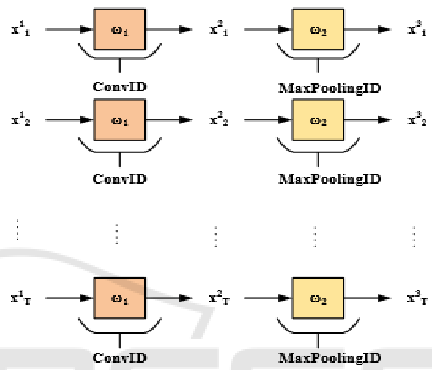

Figure 2: CNN Architecture.

Convolutional, pooling, and fully linked layers are among the layers that make up CNN. Figure 2. displays the CNN architectural diagram.

4.3.1 Input Layer

Typically, a CNN receives a picture as input in the form of an ordered set of pixel values. The physical dimensions of an image (e.g., 224 x 224 pixels for an ordinary image classification assignment) dictate the size of the input.

4.3.2 Convolutional Layer

The layer having the most powerful signature in a CNN is the convolutional layer, which is the first step in the extraction of features. The extraction of various contours from the input sensor images is the local operation's purpose, which results in an efficient classification. Convolutional layers consist of several convolutional kernels, which are the trainable parameters that vary with every iteration of the layer is shown in eqn. (2).

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n) \quad (2)$$

$S(i,j)$ represents the output of the convolution procedure at point (i,j) in the resultant feature map. I am a representation of the input matrix, which is typically a feature map or picture. The symbol K represents the convolution kernel. $\sum_m$ and $\sum_n$ indicate the total of the spatial dimensions of the kernel. The symbol $(i+m, j+n)$ represents the pixel value of the input matrix at location$I(i+m, j+n)$. $K(m,n)$ represents the quantity (or filter coefficient) inside the convolution kernels at position (m,n). CNNs usually have a large number of convolutional layering in an attempt to identify more distinct patterns of space in the input images. Keeping the image sizes constant throughout the process is ensured by employing zero padding in conjunction with convolutional layers.

4.3.3 Pooling Layer

Let $G_i^n \in R^{M^n \times N^n \times D^n}$ be the input of the N-th layer, which is essentially a layer for pooling that has a longitudinal range of $m' \times n$'. These layers are parameter-free since they don't have any variables that need to be learned. They assume that m' divides M, n' divides N, and stride matches the pooling longitudinal span. The outcome is represented as $Y^n \in R^{M^{k+1} \times N^{n+1} \times D^{n+1}}$, which is a tensor of order three given in eqn. (3),

$$M^{n+1} = \frac{M^n}{m}, N^{n+1} = \frac{N^n}{n}, D^{n+1} = D^n \quad (3)$$

In contrast, each G_i^n channel is handled separately and one at a time by the pooling layer. Although there are numerous distinct pooling techniques, the most used ones are average and maximal pooling. When max-pooling was used in the study, the outcomes followed an eqn. (4):

$$y_{i^n, j^n, d} = G^n_{i^n \times m * + i *, j^n \times n * + j *, d} \quad (4)$$

It seems natural that pooling layers could be used to minimize output tensor size while maintaining the most significant detected characteristics where $0 \leq i^{n*} \leq M^{n*}, 0 \leq j^{n*} \leq N^n$and $0 \leq d \leq D^n$.

4.3.4 Fully Connected Layer

This layer, referred to as another portion of the CNN, functions by successfully sorting the features that were obtained by the first component. The input of the primary fully linked layer is a highly dimensional vector that contains each feature that was extracted and created as the outcome of a smoothing procedure. After the last completely linked layer, a classification operation (soft max, sigmoid, tanh, etc.) is always applied. With the selected loss function, the actual value y_j is contrasted to the expected valuey_j, applying the sigmoid function in this case is given as eqn. (5).

$$y_j = \frac{e^{G_j}}{1+e^{G_j}}, \ G_j \in R \quad (5)$$

Where, the output $G_j \in R$ is frequently utilized in neural networks. This function is appropriate for issues with binary classification since it converts an input, G_j, through a value that ranges from 0 to 1. e^{G_j} is the term that is the increasing function, and e^{G_j} is the denominator, makes sure the result is a legitimate probability. Based on the input G_j, the result y_j can be interpreted as the probability of a binary event.

4.3.5 Rectified Linear Unit

Another crucial idea is dropout, a strategy for making the learning process more universal while lowering the possibility of overfitting. It brings back to zero the configurations associated with a given number of network nodes. Lastly, the processes of batch normalisation and Rectified Linear Unit (ReLU) function as essential transitory mechanisms connecting the aforementioned stages. The ReLU function's description is given in eqn. (6).

$$y_{i\prime, j\prime, d} = \left(0, G^{n\prime}_{i\prime, j\prime, d}\right) \quad (6)$$

Batch regularisation increases the speed and stability of neural networks by regularising the layer's input by rescaling and re-centering it after each iteration. It does this by trying to transfer only the elements required for the classification using $0 \leq i \leq M\verb|^|n, 0 \leq j \leq N\verb|^|n, and\ 0 \geqq d \leq D\verb|^|n.$

4.3.6 SoftMax Layer

In Convolutional Neural Networks as well as other neural network topologies, the SoftMax layer is an essential component, particularly in classification tasks. Since the output layer, is usually utilized to convert the network's basic output values into probability distributions across several classes. The outcomes are guaranteed to be balanced and to indicate probability by the SoftMax function. Eqn. (7) provides the SoftMax layer formula.

$$fi = \frac{u^{a_x}}{\sum_{y=1}^{m} u^{a_x}} \quad (7)$$

The basic logarithm, or Euler's number, has a base of u, and the initial score or logit for class a is represented by a_x. $\sum_{y=1}^{m} u^{a_x}$ represents the total exponentiated logarithms for all classes.

4.4 Transfer Learning

Transfer learning in CNN representations has demonstrated that CNN layers may be applied from natural images to various medical data, including CT (computed tomography) images, ultrasonic data, and neuroimaging data, either by fine-tuning the settings or by using the pre-made models. The term "transfer learning" relates to a method of machine learning that enables knowledge from one domain to be applied to related domains and issues. It is advised to start a task that is identical to the trained model by using the model that was created and trained for that task. In order to define transfer learning, researchers have employed a variety of notations to explain its various principles. The two fundamental ideas of transfer learning are domain and task, both of which have mathematical explanations. To help with clarity, transfer learning is explained arithmetically. The two components that makeup Domain M are the marginal distribution H (G) and the feature space which is shown in eqn. (8).

$$M = g, H(G) \quad (8)$$

G is an occurrence set (also known as an instance set) in this case, and it can be understood as $G = \{y|y_j \in g, j = 1, .., n\}$. Task T consists of a label space L and a judgment function t of eqn. (9).

$$A = \{B, a\} \quad (9)$$

Utilizing pre-trained models' expertise from general image recognition tasks and tailoring it to the particular job of optical sensor image classification is known as transfer learning. This approach is used to improve optical sensor image classifications through deep learning with CNNs. To start, a CNN model that has been previously trained is initialized. The pre-trained model's convolutional layers function as efficient feature extractors, identifying subtle and intermediate visual patterns. The pre-trained model's last layers are changed or replaced in the adaption step to correspond with the number of categories in optical sensor images. Next, fine-tuning is performed on the newly created dataset of tagged optical sensor images by minimizing the cross-entropy loss is given in eqn. (10).

$$O = (x, \widehat{x}) = -(x \log(\hat{x}) + (1 - x) \log(1 - \hat{x})) \quad (10)$$

Where x is the real label (0 or 1) and xˆ is the expected probability of a class that is positive. The cross-entropy loss is used to quantify the difference between the true labels of the fresh dataset and the anticipated class likelihoods when fine-tuning a CNN for optical sensor image classification. By changing the model's weights, the goal of fine-tuning is to reduce this loss as much as possible. Gradient descent and other optimization algorithms are used to iteratively update the weights during the fine-tuning process, which enables the model to adjust to the unique properties of the optical sensor dataset. Through this procedure, the model's weights can be changed to focus on characteristics important for classifying land cover. After that, the modified model is trained using the particular optical sensor dataset, which includes both labelled and unlabelled data in order to improve generalisation. Through transfer learning, the model gains access to the wealth of information stored in previously trained models, greatly enhancing its effectiveness, precision, and flexibility in responding to the particulars of optical sensor picture.

5 RESULTS AND DISCUSSION

The results show significant gains in the precision and effectiveness of optical sensor image classification in the study of Improving Optical Sensor Image Classification through Deep Learning with CNN. By utilizing CNNs, the model demonstrated better performance in identifying complex characteristics from optical sensor images, which improved classification results. The performance metrics of several image classification techniques, such as Fuzzy C Means, Segmentation and Classification Tree, Region-based GeneSIS, OBIA, Knowledge-based Method, as well as the Proposed CNN along with Transfer Learning, are included in the results that are presented. The evaluation metrics highlight each method's effectiveness, including recall, accuracy, precision, and F1 score. It's crucial to remember that these outcomes were achieved via simulation, highlighting the stability and dependability of the suggested CNN along with Transfer Learning strategy in a safe virtual setting. Even with a small amount of labeled optical sensor data, the model was able to adapt and perform well in the classification job thanks to the use of transfer learning. By minimizing the cross-entropy loss on the fresh data set, the fine-tuning procedure demonstrated the model's capacity to pick up on and become an expert in the subtleties of optical sensor properties. The approach used, which included data augmentation and normalization, strengthened the model's ability to handle a variety of optical sensor settings. Overall, the findings highlight the effectiveness of deep learning, especially CNNs, in expanding the area of optical sensor picture categorization and opening doors for more precise and trustworthy optical sensor data analysis across a range of applications.

5.1 Outcome of Optical Sensor Image Classification through Deep Learning with CNN

Convolutional neural networks are used to accurately classify images as a result of deep learning with optical sensor image classification. To provide more accurate item and scene classification and identification for optical sensor-captured images, this approach makes use of sophisticated patterns and features that have been learned from data.

5.1.1 Training and Validating the Datasets

A validation and training dataset is generated for every optical sensor image. The following is the labelling of the datasets: Land: 1, Forest: 2, Water: 3. After that, gaining access to the training datasets via the "Datasets" subdirectory.

The datasets to be trained for every optical sensor image are located in the 4-D array Figure 3. shows the XTrain Dataset, which has pictures with dimensions of 2x2x3xNumber_of datasets. The image has two dimensions: height and width. The Figure 4. Shows the RGB image has three channels. The total number of datasets generated for every optical image is the last component.

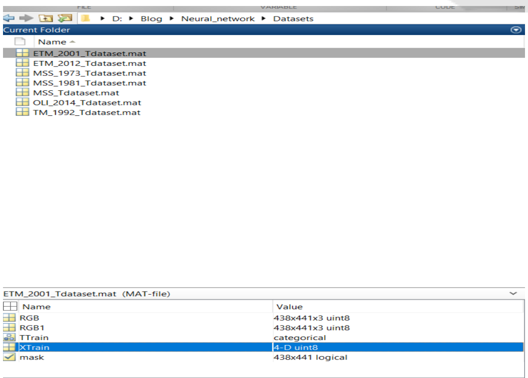

Figure 3: XTrain Dataset.

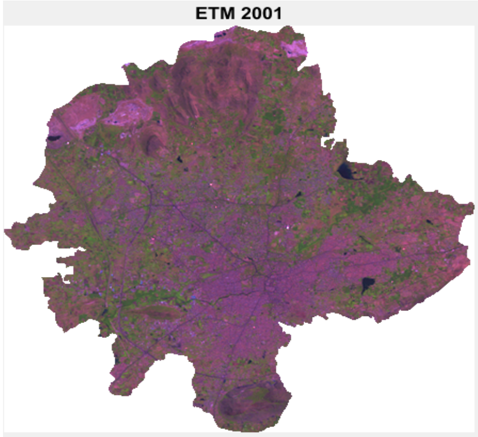

Figure 4: RGB Image.

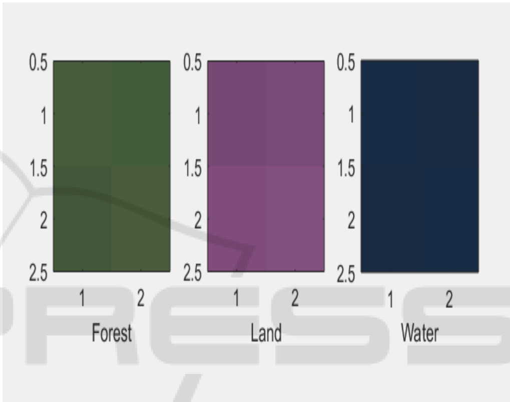

Figure 5: Training Datasets for Optical Sensor Images.

The datasets generated from the optical sensor for training are displayed in Figure 5. The class of every 2x2x3 dataset mentioned above is contained in the categorized array known as "TTrain."

5.1.2 Training the Convolutional Neural Network

Constructing every layer in a way that trains the network. The initial input was the image layer. Enter the size of the dataset, for example, 2x2x3 [2 for height and breadth and 3 for channels since RGB]. Second place goes to the 1x1 convolution layer, which includes three filters. The classification layer, max pooling, SoftMax, completely connected, fully connected, and the Rectified Linear Unit (ReLU) function come after it.

5.1.3 Validating the Trained Datasets

In this validation stage, the accuracy of the network that was trained will be assessed by testing 20 randomly selected samples against the trained network. The 20 randomly chosen samples are displayed in this image, together with the expected and correct labels for each dataset. (Labels: 1 for Forest, 2 for Land, and 3 for Water).

Figure 6: Confusion Matrix.

In a classification model, the confusion matrix shows a visual comparison between the actual and predicted labels. It has four labels (1, 2, 2.2, 3.3) represented by four rows and columns. Every cell displays the number of times a predicted label (columns) was incorrect (rows). Figure 6 shows the confusion matrix. The model's accuracy and mistakes are measured by real positives, real negatives, false positives, and false negatives.

5.1.4 Testing the Datasets

```
*************Loading the datasets***************************
Dataset Name:OLI_2014_Tdataset.mat
*************Training the Network***************************
Training on single CPU.
Initializing image normalization.
|==========================================================================|
|   Epoch    |  Iteration  | Time Elapsed | Mini-batch  | Mini-batch  | Base Learning|
|            |             |  (seconds)   |    Loss     |  Accuracy   |     Rate     |
|==========================================================================|
|          1 |           1 |        0.10 |      1.1025 |      42.97% |       0.0100 |
|         17 |          50 |        1.30 |      0.2372 |      99.22% |       0.0100 |
|         30 |          90 |        2.03 |      0.1043 |     100.00% |       0.0100 |
|==========================================================================|
*************Validation*************************************
Accuracy:0.95
*************Test the dataset*******************************
Elapsed time is 3.349816 seconds.
```

Figure 7: Validation Dataset.

The network that was trained will be used to test the RGB image, and the output will be the final categorized data. Following dataset selection, training, and validation will occur. A calculation of 0.95% is performed for accuracy using the validation dataset shown in Figure 7. Additionally, the accuracy is computed after testing the twenty datasets that were selected at random.

5.1.5 Final Output

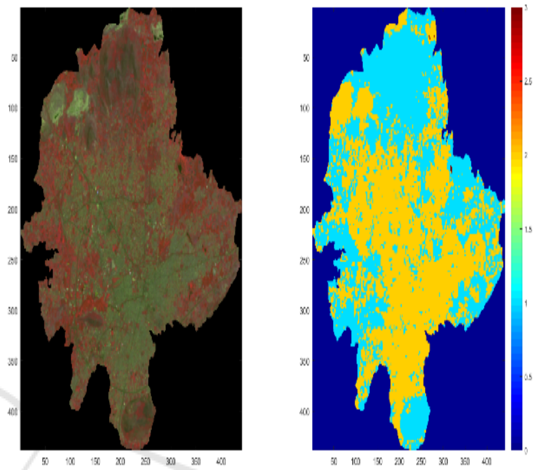

Figure 8: Comparative Representation of Land Features.

The Figure 8. contrasts two images, most often pertaining to environmental or geographic information. The continent with colored topography is seen in the left image. The data is visualized utilizing a scale of colors in the right image, which might indicate variables like height or temperature.

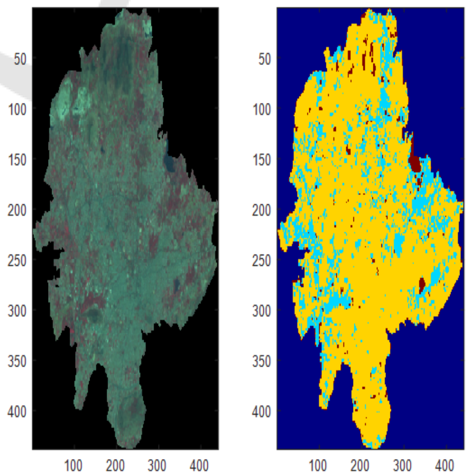

Figure 9: Comparative Evaluation of Vegetation Density.

Figure 9. Shows two different visual depictions of the density of vegetation in a given area are shown in

this illustration. Although the right image represents a processed version that uses color codes to emphasize areas of different vegetation density, the left image looks to be an aerial or satellite view. The map on the left displays an aerial as well as satellite perspective, with varying green tones signifying different vegetation types. The color-coded map on the right most probably shows varying degrees of density of vegetation or health, having yellow and blue reflecting these levels. Plotting both maps on a grid, the x and y axes have numerical scales from 50 to 400 along them.

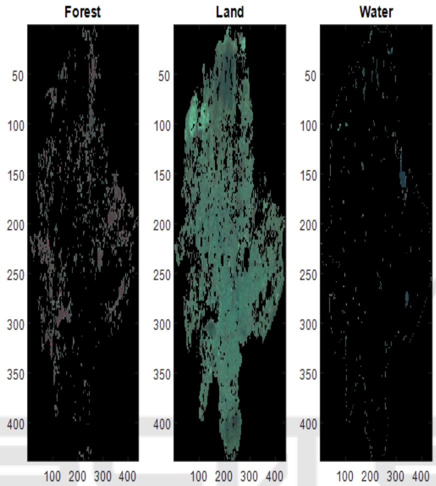

Figure 10: Optical sensor image classification of proposed CNN and transfer learning method.

The output images from the suggested work demonstrate a remarkable achievement within optical sensor image categorization, demonstrating the model's ability to identify and classify various types of land cover. It is shown in Figure 10. The photos are successfully categorized into different groups like land, water, and forest, proving the reliability of the suggested CNN along with Transfer Learning approach. The model's capacity to extract complex patterns and features that occur in optical sensor pictures is demonstrated by the clarity and accuracy with which these classes can be distinguished. The accurate classification's visual representation highlights the usefulness of the suggested method and provides insightful information for applications in geospatial analysis, land use planning, and environmental monitoring.

5.2 Performance Evaluation

The study employed four assessment metrics are F1-score, accuracy, precision, and recall to analyse the designs. These particular variables are denoted by the numbers (11), (12), (13), and (14):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

$$Recall = \frac{TP}{TP+FN} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$F1score = \frac{2*Recall*Precision}{Recall+precision} \quad (14)$$

TP is the total amount of information that was accurately identified as positive, regardless of the sort of information that was positive. TN is the total amount of data that was correctly classified as negative even though none of the outcomes were actually negative. The letter FN stands for the number of variables for which the formula was wrongly classified as negative even though the input data showed them to be positive. False positives, or FP, are the number of values that the algorithm misclassified as positive even though they had been negative in the original data. Recall is the ratio of the amount of positive results that the algorithm determined to be relevant to the overall amount of positive results that were actually found during data collection. The ratio of all the data that the model correctly classified as positive to the total number of data that the algorithm classified as positive is known as precision. Finally, as previously stated, the F1-score is the harmonic mean of recall and precision. Best of Class.

Table 1: Performance metrics of proposed CNN and transfer learning model is evaluated with existing methods.

Method	Accuracy	Precision	Recall	F1 Score
Fuzzy C Means	68.9%	67%	66%	65%
Segmentation and classification tree method	70%	69.2%	68%	69%
Region-based GeneSIS	89.86%	88%	87%	88%
OBIA	93.17%	93%	92%	92%
Knowledge-based Method	93.9%	92%	91%	93%
Proposed CNN and Transfer Learning	95%	94.9%	93%	94.5%

Table 1 shows a comparison of the suggested CNN and Transfer Learning model's performance metrics with those of the current techniques for classifying optical sensor images. A comparative analysis of several image classification techniques, such as the Proposed CNN along with Transfer Learning, Region-based GeneSIS, OBIA, Segmentation along with Classification Tree, Fuzzy C Means, and Knowledge-based Method, is presented in the table. The suggested method performs better than the others, as evidenced by the metrics accuracy, precision, recall, as well as F1 score, which show outstanding precision accuracy of 95%.

The findings displayed in Figure 11 demonstrate the exceptional efficacy of the suggested model, exhibiting a 95% accuracy rate, 94.9% precision rate, 93% recall rate, and 94.5% F1 score. By contrast, state-of-the-art approaches like Region-based GeneSIS & Object-Based Image Analysis (OBIA) perform admirably, whereas conventional approaches like Fuzzy C Means and Segmentation and Classification Tree show reduced accuracy and precision. Nevertheless, the knowledge-based strategy and the suggested CNN and Transfer Learning frameworks surpass the others, highlighting how deep learning techniques can improve optical sensor image categorization problems.

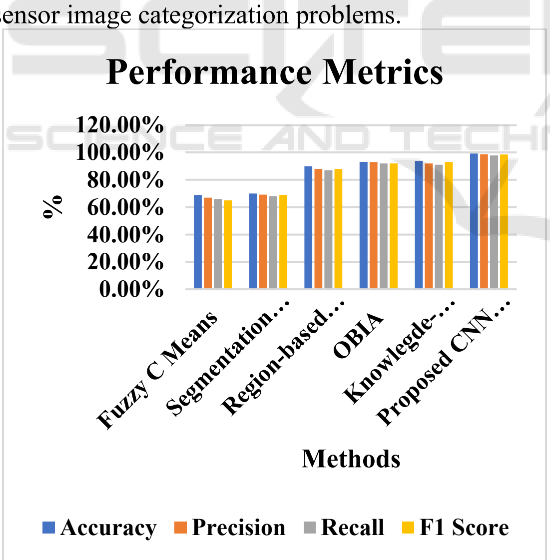

Figure 11: Graphical representation of proposed method compared with existing methods.

The training log displayed offers valuable insights into the deep learning model's training process, including information on epochs, iterations, and time elapsed is shown in Table 2. An epoch is a single run over the whole training dataset, and the number of batches processed in an epoch is represented by its iterations. Time elapsed shows how long the training has taken overall up until a certain stage. Mini-batch precision and loss display the results of each iteration's effectiveness using a subset of data. The initial learning rate used to modify model weights through optimization is reflected in the base learning rate. The model's development is demonstrated in the log, with rising accuracy and falling loss, two important measures to assess how well the training procedure improved the classification of optical sensor images.

Table 2: Proposed CNN and transfer learning model performance.

Epoch	Iteration	Time Elapsed	Mini-batch	Mini-batch	Base Learning
		(hh:mm:ss)	Accuracy	Loss	Rate
1	1	1	50.00%	21.8185	0.0100
13	50	00:00:00	99.22%	0.4842	0.0100
25	100	00:00:00	99.22%	2.0046	0.0100
30	120	00:00:00	99.22%	1.0745	0.0100

5.3 Discussion

The proposed methodology is effective, as demonstrated by the amazing 95% accuracy achieved in Improving Optical Sensor Image categorization via Deep Learning using Convolutional Neural Networks. This high degree of accuracy shows how well the model can recognize the intricate characteristics and structures included in optical sensor images. Using CNNs, because of their hierarchical extraction of features capabilities, was essential to improving the discriminative capacity of the model. The model's ability to adapt to and perform very well in the particular subtleties of optical sensor image categorization was further proved by the integration of transfer learning, which further illustrated how good it is at utilizing prior information. The achieved accuracy shows the effectiveness of both the deep learning technique and the effective fine-tuning procedure that was led by minimizing the cross-entropy loss on the fresh dataset. The current state of sensor image classification systems is hindered by difficulties managing a wide range of environmental variations and conditions, a restricted ability to accommodate different kinds of sensors, and a reliance on sizable labelled datasets for efficient training (Kumarganesh. S and M.Suganthi, 2016) and (S. K. Mylonas et al., 2015). The ability of the suggested method to attain extraordinary accuracy demonstrates its robustness, which is important in practical situations where accuracy in the classification of optical sensor images is critical. Outstanding performance is highlighted by its flexibility, effective feature extraction using CNNs, and knowledge leveraging. Limitations include processing costs, dataset dependency, and comprehension issues with its high accuracy. Objectives include investigating data-efficient transfer learning, improving comprehension, and addressing computational economy. The field will advance through standardizing evaluation measures and dynamic adaptability to varied settings.

6 CONCLUSION AND FUTURE SCOPE

The suggested CNN and Transfer Learning approach shown remarkable efficacy in optical sensor image categorization, with a remarkable 95% accuracy rate. With the help of transfer learning to improve classification accuracy and deep learning to facilitate effective feature extraction, the model demonstrated exceptional flexibility. Remarkable accuracy, recall, and F1 score confirm its resilience in managing many situations. Although great success was attained, interpretability and computing resource issues were noted. Prospective investigations ought to provide precedence to tackling problems related to computing efficiency by use of inventive methods, delving into model compression without sacrificing precision. Improving interpretability balancing explain ability with complexity remains essential. The suggested method's use will be expanded by looking into ways to lessen the need for large, labelled datasets in order to facilitate successful transfer learning. Furthermore, the model's robustness in various optical sensor settings should be prioritized through dynamic adaptation to changing environmental conditions. The field will continue to progress through cooperative efforts to standardize evaluation measures for optical sensor image categorization techniques. All things considered, the suggested study establishes a solid framework for further efforts to maximize effectiveness, comprehensibility, and flexibility in optical sensor image classification systems.

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