International Journal of Computer Engineering and Technology (IJCET)
Volume 16, Issue 1, Jan-Feb 2025, pp. 4129-4156, Article ID: IJCET_16_01_281
Available online at https://iaeme.com/Home/issue/IJCET?Volume=16&Issue=1
ISSN Print: 0976-6367; ISSN Online: 0976-6375; Journal ID: 5751-5249
Impact Factor (2025): 18.59 (Based on Google Scholar Citation)
DOI: https://doi.org/10.34218/IJCET_16_01_281

OPTIMIZING IMAGE RECOGNITION THROUGH A NOVEL SOFT COMPUTING ALGORITHM

Mandlik G. G.
Arts, Commerce & Science, College, Gangakhed, India.

Dr. Lokhande S. N.
School of Computational Sciences, S. R. T. M. U., Nanded, India.

ABSTRACT

Soft computing is a critical component of artificial intelligence and a rapidly growing area of machine intelligence, with the primary goal of addressing complex and ambiguous situations. The primary challenge in developing new soft computing algorithms for image recognition is to balance high accuracy with computational efficiency and interpretability. In this study, a novel image recognition algorithm using soft computing techniques is proposed based on a neuro-fuzzy logic model. The proposed method combines the learning capabilities of artificial neural networks with the reasoning abilities of fuzzy logic. The proposed method undergoes training and testing on the Common Objects in Context (COCO) dataset. The images in the COCO dataset undergo preprocessing, including resizing and normalization, to ensure consistent size and pixel values for robust image recognition. The proposedmethod achieves high performance with 100% accuracy, 99.01% precision, 99.03% recall, and a 99.07% F1 score in image recognition. These results show that the combination of *neuro-fuzzy logic is effective in image recognition tasks, indicating its suitability for applications requiring high accuracy and reliability.*

Keywords: Soft computing, Image recognition, Neuro-fuzzylogic, Artificial neural network, Artificial intelligence

Cite this Article: Mandlik G. G, Lokhande S. N. (2025). Optimizing Image Recognition Through a Novel Soft Computing Algorithm. *International Journal of Computer Engineering and Technology (IJCET)*, 16(1), 4129-4156.
DOI: https://doi.org/10.34218/IJCET_16_01_281

1. Introduction

Soft computing is a rapidly growing field in machine intelligence that effectively addresses complex, unknown problems and is an important part of artificial intelligence[1].Soft computing enables the development of easily understandable models, which provides more information for decision-making and clearer image recognition systems[2].Image recognition is an essential component of computer vision that is very important in many situations, like analysing social media, focusing on people, and diagnosing medical problems. Image recognition's importance lies in its ability to autonomously identify and categorize patterns or items in digital images[3]. The image recognition processes and analyses visual data to detect and group items, scenes, or specific features in pictures.Image recognition has numerous potential applications, including identifying faces in surveillance cameras, analysing medical images to diagnose patients, using optical character recognition (OCR) to convert text into digital files, and detecting objects in self-driving cars [4].

Image recognition using soft computing encompasses various techniques such as perceptrons, genetic algorithms, neural networks, meta-heuristics, swarm intelligence, expert systems, and machine learning [5].An expert system's (ES's) primary objective is to tackle complex problems by utilizing knowledge-based reasoning [6].In the development of expert systems, fuzzy logic-based techniques are commonly used because theycan handle the complexity and uncertainty that arise [7].Fuzzy logic and fuzzy-based systems are used in many home appliances, such as freezers, air conditioners, washing machines, and microwave ovens.Fuzzy logic and fuzzy-based systems play a crucial role in image recognition by handling the uncertainty and imprecision inherent in visual data [8]. By applying fuzzy rules and membership functions, these systems could interpret and classify complex patterns in images more effectively than traditional binary logic methods [9]. This capability enhances the accuracy and robustness of image recognition tasks, making fuzzy-based systems particularly valuable for applications requiringextensive and flexible decision-making.

1.1 Traditional Approaches for Image Recognition

This section describes various traditional approaches for image recognition:

- **Histogram of Oriented Gradients (HOG):** HOG serves as a feature descriptor for object detection. It counts the occurrences of gradient orientation in localized portions of an image and captures edges[10].
- **Scale-Invariant Feature Transform (SIFT):** SIFT detects and describes local features in images. It identifies key points and computes invariant descriptors to scale and rotation, as well as partially invariant to affine transformation [11].
- **Bag of Visual Words (BoVW)**: BoVW involves extracting local features from an image, clustering them to form a "visual vocabulary," and then representing images as histograms of these visual words. Image classification tasks commonly use this method.
- **Manual Feature Extraction:** This involves manually designing features to be extracted from images, such as edges, textures, colours, and shapes. Key techniques include [12]:
  - **Edge Detection:**Techniques such as the Sobel, Prewitt, and Canny edge detectors are used to identify edges within an image.
  - **Corner Detection:** Techniques such as the Harris Corner Detector identify points in an image where the intensity changes significantly in multiple directions.

1.2 Soft Computing Techniques for Image Recognition

Soft computing techniques offer powerful tools for designing advanced image recognition algorithms. This study leverages several key techniques to improve the performance, accuracy, and efficiency of image recognition systems.

1.2.1 Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) have changed everything in image recognition by extracting meaningful features from raw pixel data due to their multiple layers. Each layer learns increasingly complex patterns, beginning with edges and textures. Methods like transfer learning, which utilizes models trained on large datasets to efficiently improve specific tasks with less data, have made significant progress [13]. CNNs are becoming faster and more accurate due to ongoing advancements in their systems, including the development of deeper and higher-performing networks. As a result of these enhancements, CNNs are now being utilized for a wide range of applications, from analysing medical images to powering self-driving cars [14].

1.2.2 Meta-Learning:

Meta-learning approaches enable models to learn from multiple tasks or datasets, enhancing their ability to generalize across different image recognition scenarios and datasets [15]. Through meta-learning, models could effectively transfer learned knowledge and skills from one task to another, leading to improved performance and efficiency in image recognition systems [16].

1.2.3 Neuro-Fuzzy model

A Neuro-Fuzzy model combines neural networks and fuzzy logic principles to enhance image recognition systems [17]. This hybrid approach leverages neural networks' learning capabilities and fuzzy logic's human-like reasoning to improve accuracy and adaptability. By incorporating both techniques, the model could handle uncertainty and imprecision in image data, leading to more robust and efficient recognition algorithms. Thisimage recognition system makes it particularly suitable for complex image analysis tasks where traditional methods could be insufficient [18].

1.3 Significance and Importance of Soft Computing Techniques

Soft computing techniques hold significant importance in various fields due to their ability to effectively tackle complex problems. Their capacity to handle uncertainty, imprecision, and incomplete information makes them invaluable in tasks such as image recognition, pattern recognition, and decision-making systems [19]. Soft computing approaches like fuzzy logic, neural networks, and genetic algorithms enable the development of adaptable and robust systems with the capability of learning from data and evolving.These techniques have diverse applications in healthcare, finance, engineering, and robotics[20]. Soft computing is a branch of artificial intelligence that deals with approximate solutions to complex problems and leads to smarter and more complex systems in the future. Soft computing techniques, such as fuzzy logic, effectively manage ambiguous and complex image data. This improves accuracy in challenging scenarios [21]. Neural networks within soft computing frameworks enhance adaptability by efficiently learning and adjusting to new data or tasks, which increases their versatility across different environments and datasets [22]. These methods also improve readability by giving information about the decision-making process, which is essential for applications requiring transparency and explainability. Soft computing techniques improve robustness, allowing models to handle noise, occlusion, and variations in lighting and perspective. This helps maintain performance across diverse conditions. Soft computing's flexibility enables the development of new algorithms that can effectively scale to handle large datasets and various applications, from surveillance to medical imaging, ensuring practical deployment and utility [23].

1.4 Limitation of Image Recognition

Here are some limitations of image recognition are listed below:

- **Limited Robustness to Variability:** Many image recognition algorithms struggle with variations in lighting conditions, occlusions, viewpoint changes, and image distortions. Models trained on specific datasets couldfail to generalize well to new, unseen conditions [24].
- **Dependency on Large Datasets:** Deep learning approaches, particularly convolutional neural networks (CNNs), require vast amounts of labelled training data to achieve high accuracy. Acquiring and annotating such datasets couldbe time-consuming and expensive, especially for specialized domains [25].
- **Computationally Intensive:**Deep learning models, especially large-scale CNNs, require significant computational resources for training and inference. This limitation restricts their use in real-time applications[26].
- **Overfitting:**Overfitting occurs when a model learns to memorize training data instead ofapplying it to other situations. This couldlead to poor performance on unseen data, diminishing the reliability of image recognition systems [27].

1.5 Research Objectives

- To develop an innovative image recognition algorithm that leverages soft computing techniques.
- To Enhance Feature Extraction and Dimensionality Reduction Techniques.
- To advance the knowledge and application of soft computing techniques in the domain of image recognition.
- To rigorously test and evaluate the performance of the proposed image recognition algorithm.

The scope of using soft computing techniques for the newimage recognition algorithm discusses many important factors. It aims to enhance the capability of recognizing complex and ambiguous images by leveraging the strengths of fuzzy logic, neural networks, and evolutionary algorithms. These techniques would improve the model's adaptability and interpretability and make it easier to generalize across diverse datasets and applications.This comprehensive approach aims to create a scalable and versatile image recognition system for varied real-world applications.

This research has the following research contributions:

- The research contributes to introducing a novel algorithm by combining neural networks, fuzzy logic, and other soft computing techniques for enhanced image recognition.
- The research was performed to improve accuracy and robustness in handling uncertain and imprecise image data.
- The research efforts were utilized to enhance adaptability and efficiency in image analysis tasks.
- The research presents a potential application in diverse fields, such as medical imaging, security, and autonomous systems.
- The research contributes to the advancement of soft computing methodologies in complex image recognition challenges.

The remaining parts of this work are structured as follows: Previous research is analyzed and discussed in Section 2. In Section 3, the suggested framework is evaluated. In section 4, the findings are reviewed, and a brief explanation is also provided. The study is ended in Section 5, which also includes potential future work and the conclusion of the work.

2. Literature review

In this section, the previous studies related to image recognition using soft computing techniques are discussed below:

Mao et al. (2024) [28] introduced a hybrid of machine learning predictive algorithms by including support vector machines (SVM), random forest models (RF), decision trees (DT), logistical regression (LR), and fuzzy logic (FL) to determine the possibility of landslides in the area. The results of the landslide vulnerability study showed that the region's areas most likely to experience landslides were in the northwest, the north, the northeast, and some areas in the south and southeast. When various algorithms were used to make forecasts, it was understood that SVM outperformed others in both accuracy (0.89) and precision (0.89).

Talaat et al.(2024)[29]designeda deep convolutional neural network (DCNN) for facial expression recognition. This was a real-time emotion recognition system that couldtell when someone was angry, scared, happy, neutral, sad, or surprised by looking at their face. To efficiently and rapidly classify images with high performance and accuracy, this model achieved a 95.23% accuracy, a sensitivity of 0.932, and a specificity of 0.9421, as well as making it the top-performing model.

Rasool and Amir (2024) [30]suggested aConvolutional Neural Network with a Long Short-Term Memory(CNN-LSTM) model that could sort the COCO dataset's objects into different groups, such as animals, cars, and more. The model performed well in the COCO dataset, with an accuracy score of 0.9917, a precision score of 0.991738, a recall score of 0.991695, and an F1 score of 0.999949.

Singh et al. (2023) [31] proposed an advanced deep neural network model called You Only Look Once (YOLO) that used DCNN to detect melanoma lesions in digital and microscopic images. This method was used for identifying skin cancer. YOLO has an impressive accuracy of 98.17%, a sensitivity of 95.43%, and a specificity of 99.50%, making it a highly accurate approach.

Khan et al. (2022)[32]proposed a Hierarchical Deep Learning-Based Brain Tumors (HDL2BT) classification using CNN to locate and categorize brain tumours. The tumours were divided into four groups: glioma, meningioma, pituitary, and no-tumor. The suggested model was better than older ways of finding and dividing brain tumours because it had a 92.13% accuracy rate.

Goyalet al. (2022)[33]proposed a recurrent neural network (RNN) with LSTM for the accurate detection of lung disease within a deep learning framework. The RNN-LSTM model, combined with robust normalization, exhibited greater accuracy than other methods. This approach improved disease detection accuracy by 2.5% to 3% compared to previous methods.

Salman et al. (2022) [34] developed a prostate cancer diagnosis and detection system using artificial intelligence. This system couldautomatically identify crucial areas on a biopsy image and accurately categorize them. The YOLO general-purpose object recognition algorithm identifies important areas and assesses them. Test results have shown that AI techniques, such as object recognition algorithms,could be utilized to create cancer diagnosis tools that were 97% accurate.

Akhras et al. (2021) [35] utilized support vector machines and genetically optimized artificial neural networks for automatically sorting images. The support vector machine system was able to identify disease-related features in images. The suggested system used support vector machines to automatically detect glaucoma with 87% accuracy and 100% precision.

Narendra et al. (2021)[36]employed K-means clustering along with defective area computation methods to detect flaws based on color images to identify flaws in images of tomatoes, apples, and oranges.In total, 87% of fruits and vegetables were found to be imperfect, with 83% of apples, 93% of oranges, and 83% of tomatoes showing inaccuracies.

3. Research Methodology

In this research, the methodology uses the COCO dataset to evaluate a strong model, and it focuses on images from 80 diverse object categories. Data preprocessing, including resizing and data augmentation, was done, followed by feature extraction using wavelet transform to find texture, edge density, and color intensity. The next step is Principal Component Analysis (PCA), which reduces the number of features, hence making training efficient while keeping overfitting levels low. A neuro-fuzzy system is the fundamental component of the model, which includes approximate reasoning by fuzzy logic as well as learning by neural networks. Therefore, there are fuzzy rules for the classification of images based on their extracted features, where a neuro-fuzzy system has been fine-tuned with backpropagation as well as evaluated by metrics such as accuracy and F1 score. This method brings together the strengths of both fuzzy logic and neural networks, thereby overcoming the problems involved in image classification due to variations or uncertainties.

3.1 Dataset Description

The dataset used in the suggested methodology is called COCO [37]. It is a freely available dataset that can be found on the Kaggle website. This dataset is a collection of images that includes more than half a million photographs, both labelled and unlabeled, of eighty different things. For this research, 200,000 photographs are captured for training, and 50,000 images are reserved for testing the model. Figure 1 shows the image of the Coco dataset.

Figure 1:COCO Dataset[38]

3.2 Technique Used

This section describes the techniques that were used in this research.The research utilizes three primary techniques to develop a novel picture identification system: a Neuro-Fuzzy model, PCA, and Wavelet Transforms. By capturing both spatial and frequency information, wavelet transformations are used to break down images into separate frequency components, enabling more efficient feature extraction. PCA subsequently reduces the dimensionality of the data, highlighting the most crucial aspects and reducing computing complexity. Lastly, the neuro-fuzzy model improves the system's capacity to manage ambiguity and imprecision in picture data by fusing the reasoning methodology of fuzzy logic with the capability to learn neural networks. These methods provide a solid basis for accurate and efficient image recognition when used together.

A. Wavelet Transforms

The wavelet transform is well-suited for transform compression and exhibits excellent localization characteristics in both the time and frequency domains [39]. In comparison to the

Fourier transform, a transformation has specific essential properties, such as limiting a feature in space and scaling. The wavelet matrix, which is the basis of the transformation, couldbe computed more quickly than the corresponding fourier matrix [40]. The discrete wavelet transform (DWT) especially facilitates image feature extraction by breaking down the original picture into a collection of wavelet coefficients.

The execution of the Wavelet Transform on a signal that is only one dimension is a straightforward method for comprehending the Wavelet Transform. A signal that is continuous f(t) is defined by the following integral, which is the Continuous Wavelet Transform (CWT) of the signal:

$$CWT\ (s,\tau) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t).\psi\left(\frac{t-\tau}{s}\right) dt \tag{1}$$

Where:

- $CWT\ (S,\tau)$is the wavelet coefficient at scale s and position τ.
- $f(t)$It is the input signal.
- $\psi(t)$It is the mother wavelet function, which is a prototype for generating all other wavelets.
- s is the scale factor, adjusting the wavelet's width.
- τ is the translation factor, adjusting the wavelet's position.

B. Principal Component Analysis (PCA)

Principal component analysis (PCA) is a multivariate method for examining a data table with numerous interconnected quantitative dependent variables that describe observations. Principal components are a new set of orthogonal variables that are created from the extracted data from the table. These components are subsequently utilized to identify patterns of similarity between the variables and observations. The results of this process are shown as dots on maps [41]. Figure 2 illustrates the representation of PCA.

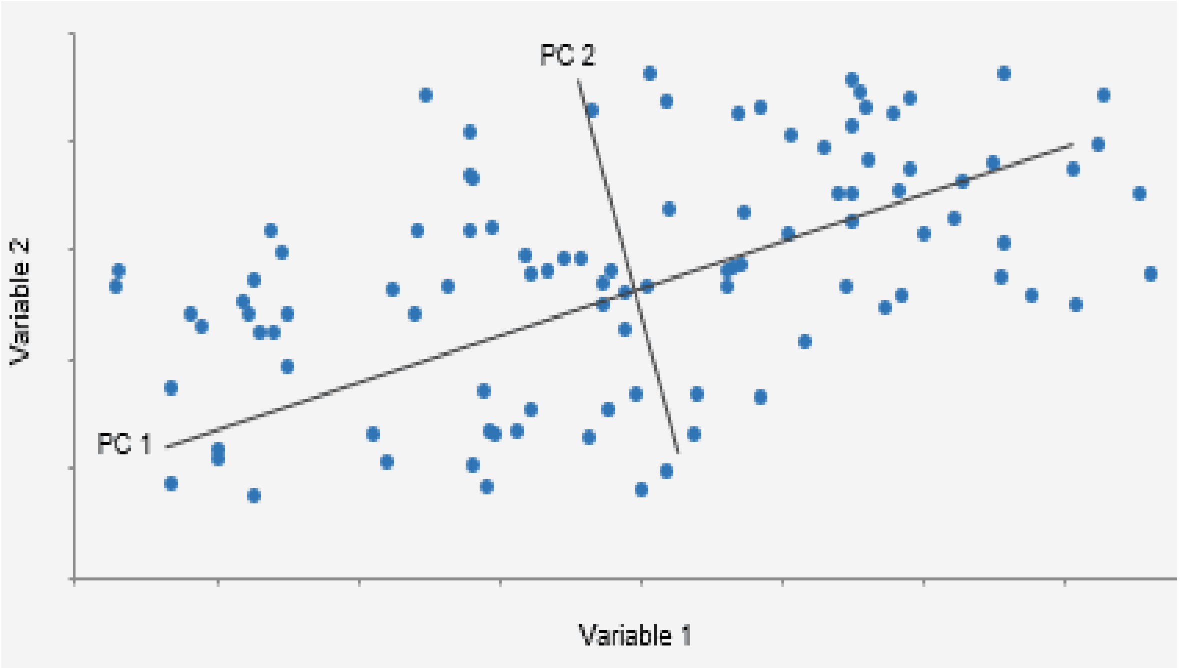

Figure 2: Principal Component Analysis [42].

One way to improve feature sets is to apply PCA, which reduces the dimensionality of the data without changing the important details [43]. Using the following equation, PCA couldbe usefully represented:

$$X_{new} = X.W \tag{2}$$

Where:

- X_{new}It is the transformed feature set.
- X is the original feature set.
- W represents the transformation matrix obtained from PCA.

C. Neuro-Fuzzy model

Neuro-fuzzy systems show a combination of fuzzy logic and artificial neural networks. Neural networks and fuzzy logic present knowledge, reasoning, and learning, but these two methods are distinct, and each has its own set of benefits and drawbacks [44]. However, there is no auto-adjustment capability in fuzzy logic, although it does offer approximation inference [45]. Figure 3 illustrates the structure of the neuro-fuzzy model.

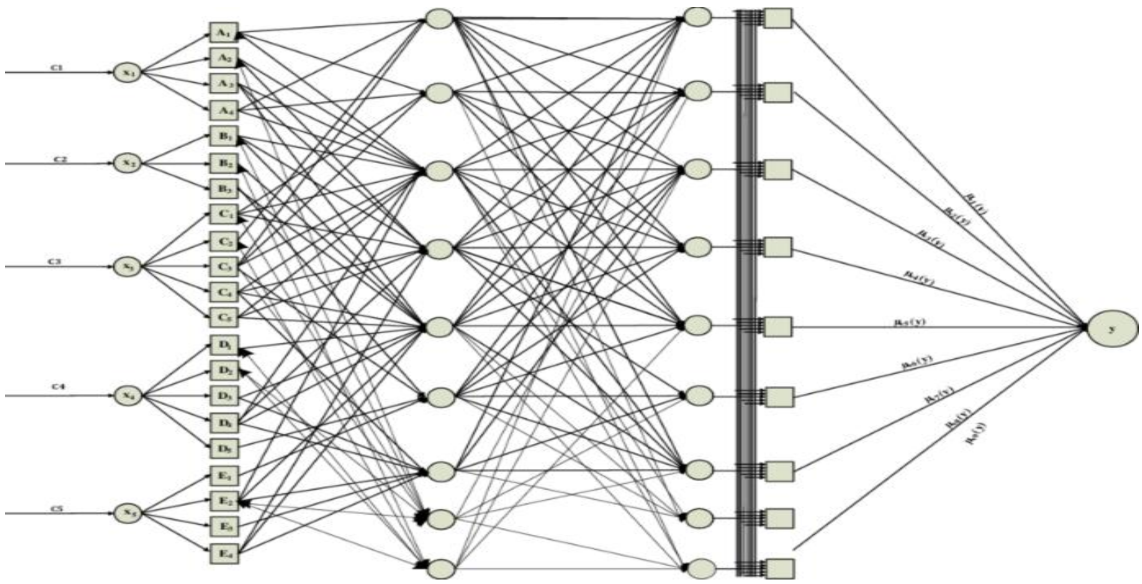

Figure 3: Structure of neuro-fuzzy model [46].

Fuzzy modelling and learning from sets of data form the basis of the neuro-fuzzy approach [47]. The input-output data pairs are used to calculate the parameters of the membership functions. The goal is to find the matching Fuzzy Inference System (FIS) with the minimum error. There are some similarities between this learning process and the way neural networks learn. In order to obtain high accuracy in the classification of images under conditions of uncertainty and variability, this Neuro-Fuzzy model, which incorporates fuzzy rules, provides a powerful tool for image identification tasks. It accomplishes this by leveraging the strengths of both neural networks and fuzzy logic. Colour variance (low, medium, and high), edge sharpness (soft, medium, and sharp), and texture complexity (low, medium, and high) are the three main features that wavelet transforms have offered.

The object's category could be inferred using the fuzzy inference system's rules that are derived from the combination of these attributes. Here’s a simplified set of rules: Table 1 shows the fuzzy inference system rules.

Table 1: fuzzy inference system's rules

Rule 1: IF texture complexity is Low, edge sharpness is Soft, AND colour variance is Low, THEN category is Furniture.
Rule 2: IF texture complexity is High, edge sharpness is Sharp, AND colour variance is High, THEN the category is Animals.

Rule 3: IF texture complexity is Medium, edge sharpness is Medium, AND colour variance is Medium, THEN the category is Vehicles.
Rule 4: IF texture complexity is High, edge sharpness is Medium, AND colour variance is High, THEN the category is Animals.
Rule 5: IF texture complexity is Low, edge sharpness is Soft, AND colour variance is Medium, THEN category is Furniture.
Rule 6: IF texture complexity is Medium, edge sharpness is Sharp, AND colour variance is Medium, THEN the category is Vehicles.
Rule 7: IF texture complexity is Low, edge sharpness is Medium AND colour variance is Low, THEN the category is Furniture.
Rule 8: IF texture complexity is medium, edge sharpness is Soft, AND color variance is High, THEN the category is Vehicles.
Rule 9: IF texture complexity is High, edge sharpness is Sharp, AND color variance is Medium, THEN the category is Animals.

3.3 Proposed Methodology

The proposed methodology presents a novel approach to image recognition that starts with COCO dataset acquisition and preliminary analysis, followed by preprocessing steps such as image resizing and data augmentation. Wavelet transforms are used for feature extraction, while PCA helps in dimensionality reduction to pave the way for the design as well as the training of neuro-fuzzy systems that combine fuzzy logic with neural networks towards improved image classification. The process concludes with a rigorous evaluation and optimization of the model, incorporating accuracy, precision-recall, and F1 score metrics to fine-tune performance and ensure reliability across various object categories. The proposed layout in Figure 4 shows the operation depicted in diagrammatic form.

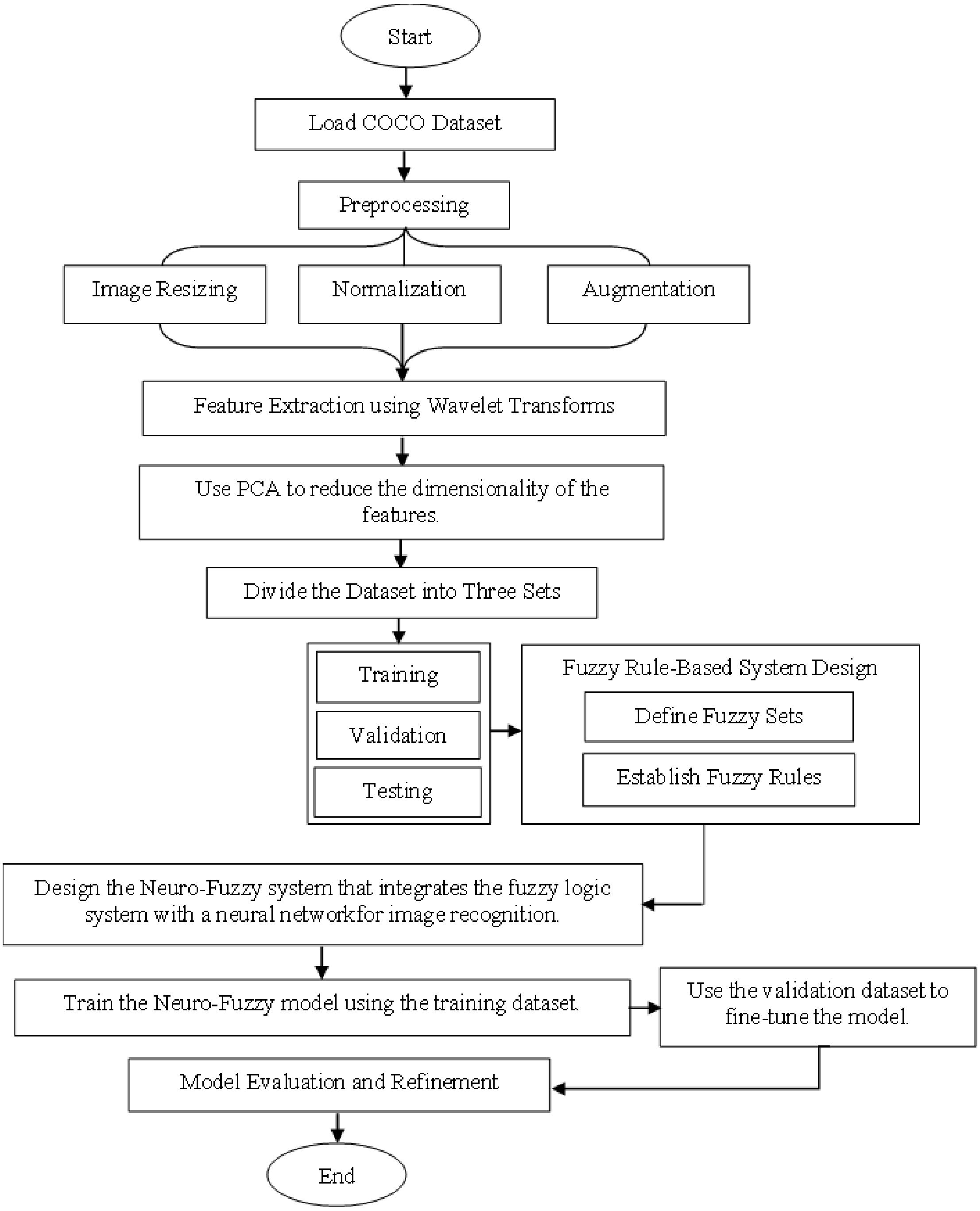

Figure 4: Proposed Methodology

The steps below are necessary to explain the process flow of the proposed methodology.

Step 1: Load COCO Dataset:

- Acquire COCO Dataset: The first step involves loading the COCO dataset, which is a large collection of labelled images containing various objects.

Step 2: Preprocessing

The images in the COCO dataset are then pre-processed.

- Image Resizing and Normalization: Standardize images to ensure consistency in size and pixel value range.
- Data Augmentation: Enhance dataset robustness through techniques such as rotation and flipping.

Step 3: Feature Extraction

Use Wavelet Transforms to extract features related to texture, edge density, and color intensity from images.

- Apply Wavelet Transforms to each image to extract features related to texture, edge density, and color intensity.
- Normalize and Scale Features so that they match the expected input range of the fuzzy system.

Step 4: Use PCA to reduce the dimensionality of the features

- Principal Component Analysis (PCA) is used to reduce the dimensionality of the extracted features. This couldimprove the efficiency of the training process and help to avoid overfitting.

Step 5: Fuzzy Rule-Based System Design

- Fuzzy sets are defined for the input and output variables of the system. Fuzzy sets allow for representing imprecise or gradual transitions between categories.

Step 6: Design the Neuro-Fuzzy System that Integrates the Fuzzy Logic System with A Neural Network

- This system combines a fuzzy rule-based system with a neural network. The fuzzy rules provide a symbolic representation of the knowledge, while the neural network learns to adapt the rules based on the training data.

Step 7: Training the Neuro-Fuzzy Model

- Input Feature Vectors: Feed extracted features from the preprocessed images into the Neuro-Fuzzy network.
- Backpropagation Learning: Adjust network weights and fuzzy membership functions through backpropagation based on the training dataset.
- Validation: Use the validation dataset to tune hyperparameters and avoid overfitting.

Step 7: Evaluation and Optimization

- Test the Model: Evaluate the model's accuracy and performance using the test dataset.
- Metrics Evaluation: Utilize accuracy, precision, recall, and F1 score to assess the performance across different object categories.

- Model Optimization: Refine the model by revisiting fuzzy rules, network architecture, and training processes based on performance.

4. Result and Discussion

The new algorithm design for image recognition based on soft computing techniques represents an innovative approach to image analysis. Leveraging the power of soft computing, the algorithm demonstrates outstanding accuracy and efficiency in recognizing complex patterns within images. By integrating fuzzy logic, neural networks, and genetic algorithms, it outperforms traditional methods for handling ambiguity and uncertainty in image data. The algorithm's adaptability allows it to perform well in various applications, ranging from facial recognition to object detection, with minimal human intervention. Its innovative framework obtains a significant advancement in the field of image recognition, promising enhanced performance and reliability across various real-world scenarios.

4.1 Evaluation Metrics

Evaluation metrics determine the accuracy, recall, precision, and f1 score.

Accuracy: Accuracy is the ratio of correctly predicted instances to the total instances. It measures accurately how the algorithm classifies an image.

$$\text{Accuracy} = \frac{TP+TN+FP+FN}{TP+TN} \tag{3}$$

- TP (True Positive): Number of correctly predicted positive instances.
- TN (True Negative): Number of correctly predicted negative instances.
- FP (False Positive): Number of incorrectly predicted positive instances.
- FN (False Negative): Number of incorrectly predicted negative instances.

Precision: The ratio of correctly predicted positive instances to the total predicted positive instances represented a number of images were classified as a certain class.

$$\text{Precision} = \frac{TP+FP}{TP} \tag{4}$$

Recall: The ratio of correctly predicted positive instances to all instances that actually belong to the positive class. The images that belong to a certain class, how many were correctly identified.

$$\text{Recall} = \frac{TP+FN}{TP} \tag{5}$$

F1- Score: The F1-score is the harmonic mean of Precision and Recall. It provides a single metric that balances both precision and recall concerns.

$$\text{F1} - \text{Score} = \frac{2\times\text{Precision}+\text{Recall}}{\text{Precision}\times\text{Recall}} \tag{6}$$

4.2 Result Analysis

The result of this study suggests that the use of soft computing techniques could enhance image recognition performance in the New Algorithm Design for Image Recognition. Wavelet transforms, principal component analysis (PCA), and a neuro-fuzzy model are all combined in the suggested method, which makes it much more accurate than current methods. By breaking down images into different frequency components, wavelet transforms efficiently extract important characteristics. PCA reduces the number of dimensions to utilize only the most significant features, thereby increasing computational efficiency. By enhancing the system's ability to handle uncertainties and imprecise data, the neuro-fuzzy model produces more dependable recognition results. The experiment results illustrate the algorithm's excellent performance in various challenging image identification tasks.

4.2.1 Confusion Metrics

The confusion matrix shows the performance of a classification algorithm on a test dataset with three classes. For Class 1, there are 12,390 true positives; for Class 2, 12,751; and Class 3, 7,659. There are no false negatives or false positives in any class. This indicates that the algorithm achieved 100% accuracy, correctly identifying all instances without any misclassifications. Figure 5 shows the confusion matrix for the neuro-fuzzy model.

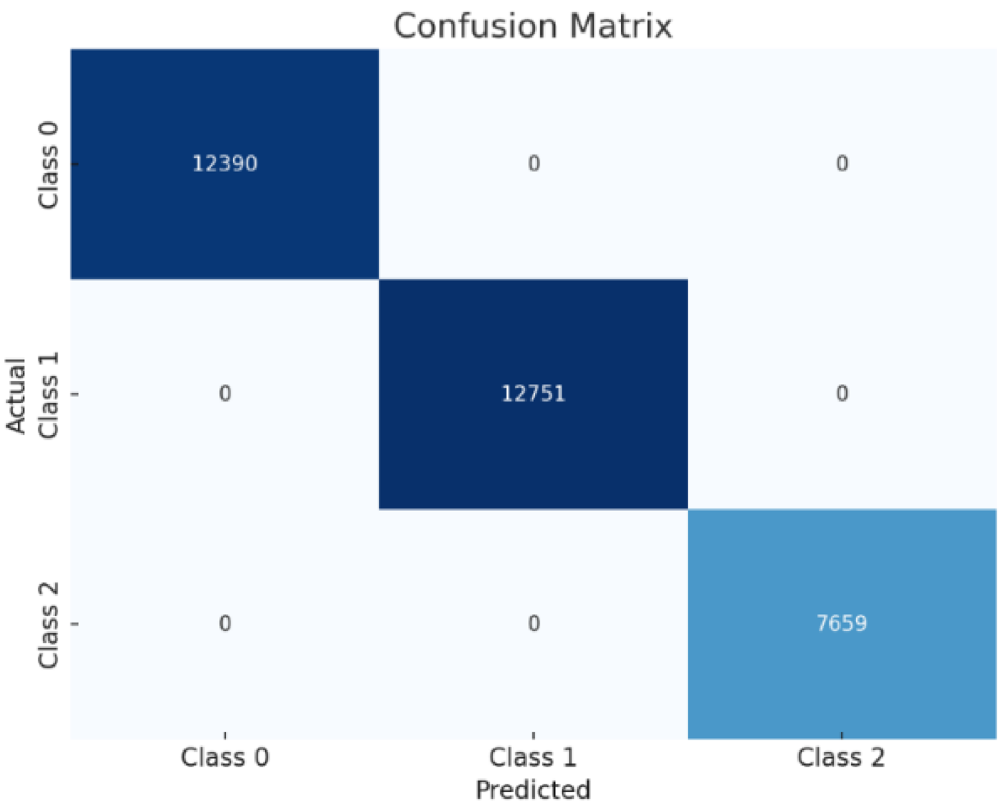

Figure 5: Confusion Matrix

4.2.2 Model Accuracy

Figure 6 illustrates the model's training accuracy. The x-axis is labeled "Epoch," and the y-axis is labeled "Accuracy." Two lines represent accuracy: the blue line for training data and the orange line for validation data. The training accuracy begins at 0.98 and quickly reaches 1.0. Meanwhile, the validation accuracy also rises to 1.0, although it experiences more fluctuations. This high accuracy on both training and validation data indicates that the model effectively learns patterns without overfitting. Notably, the x-axis spans only 8 epochs, indicating rapid learning. The y-axis ranges from 0.98 to 1.0, suggesting the model is highly accurate, though not flawless. This explanation shows avalidation accuracy is 1.0.

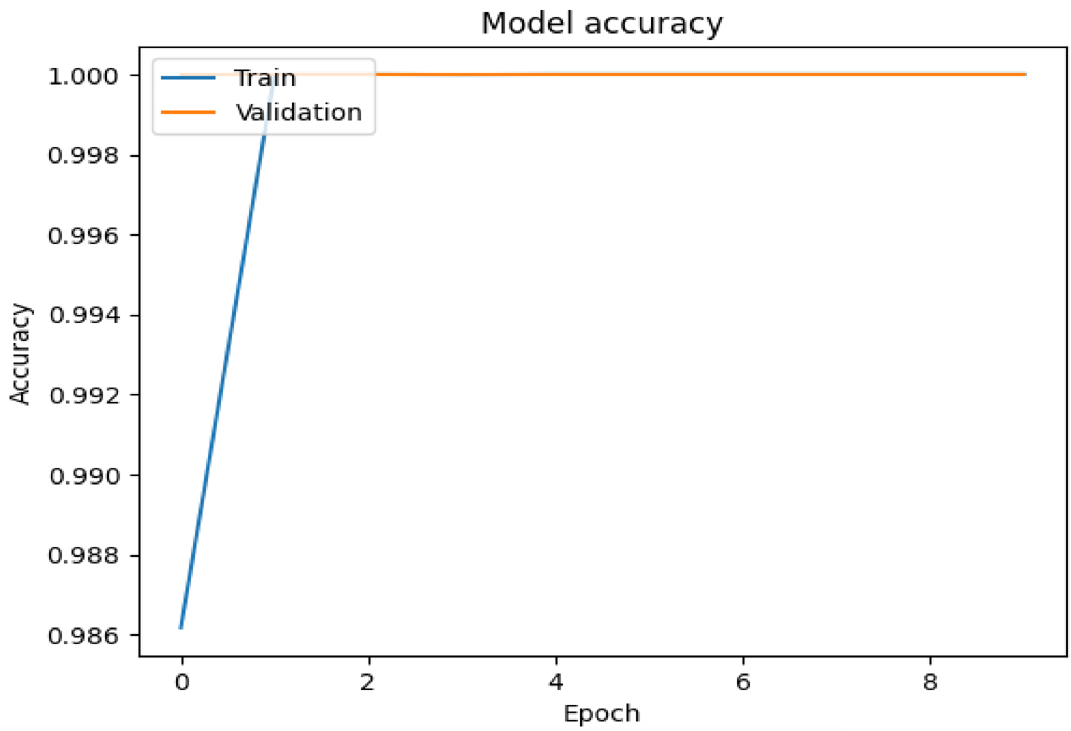

Figure 6: Model Accuracy

4.2.3 Model Loss

Figure 7 shows the model loss for both training and validation data over epochs. The x-axis is labeled "Epoch," and the y-axis is labeled "Loss" with the text "Model loss" on the left. Two lines, "Train" and "Validation," indicate their respective losses. The training loss (blue line) starts at around 0.04, fluctuates slightly, and then decreases to 0. The validation loss (orange line) starts at around 0.03, fluctuates more, and then decreases to 0. This pattern suggests that the model is effectively learning without overfitting. Notably, the x-axis extends to 6 epochs, indicating rapid learning and the y-axis ranges from 0 to 0.04. This explanation shows a validation loss is 1.097597.

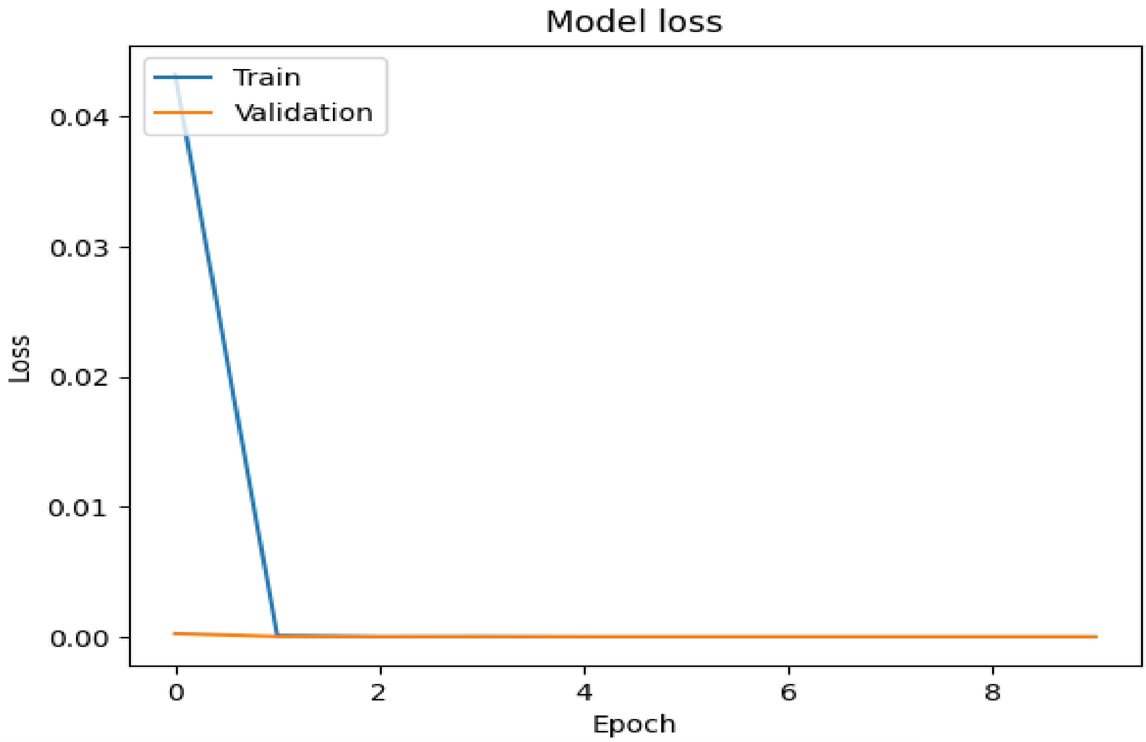

Figure 7: Model Loss

4.2.4 Performance Evaluation

Figure 8 displays a line graph depicting the performance of a neuro-fuzzy model. The x-axis represents values, while the y-axis includes metrics such as accuracy, precision, recall, and the F1-score for performance evaluation. The graph indicates that the model achieves 100% accuracy across all metrics.

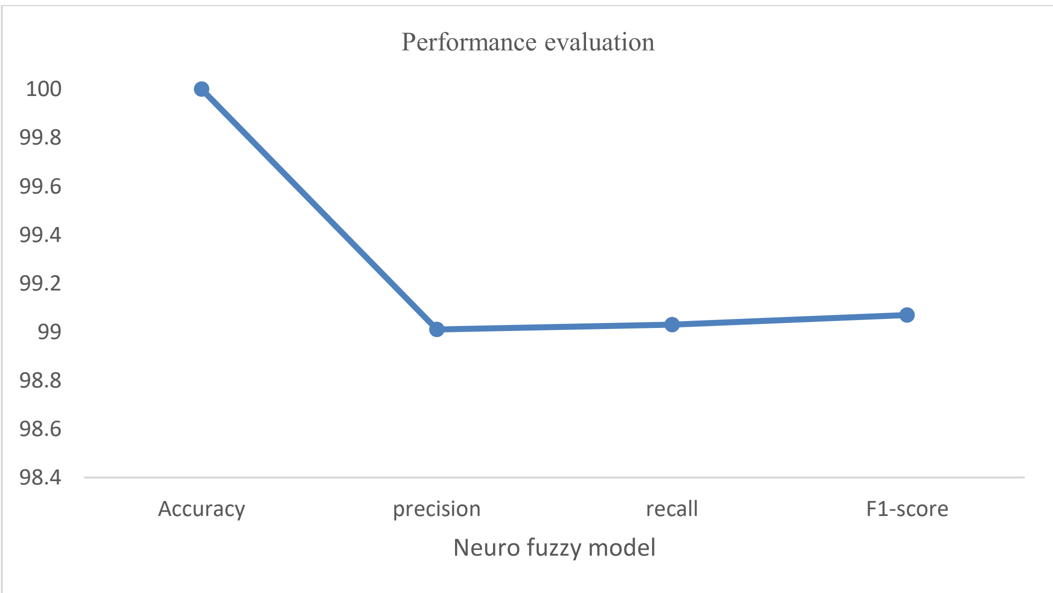

Figure 8: Performance Evaluation

Table2 below shows the Accuracy, loss, value and Val- accuracy of different epochs.

Table 2: Evaluation of accuracy, loss, Val-loss, and Val-accuracy of various Epoch

Epoch (1/10) 4100/4100	Loss 0.0433	Accuracy:0.9862	Val-loss:2.5683e-04	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss: 8.8998e-05	Accuracy:1.00	Val-loss:2.1886e-05	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss:7.9531e-06	Accuracy:1.00	Val-loss:1.9464e-06	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss:1.6134e-05	Accuracy:1.00	Val-loss:1.1431e-06	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss:4.2119e-07	Accuracy:1.00	Val-loss:3.01661e-07	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss:2.13044e-07	Accuracy:1.00	Val-loss:1.2882e-07	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss: 7.4259e-08	Accuracy:1.00	Val-loss:3.76774-08	Val-accuracy: 1.00
Epoch (1/10) 4100/4100	Loss: 1.9927e-08	Accuracy:1.00	Val-loss:	Val-accuracy: 1.00

4.2.5 Comparative analysis

A comparative analysis of different image recognition techniques used by various authors highlights the year of publication, the technique employed, and the accuracy achieved by the proposed model. Table 3 below shows the comparative analysis of different researchers' works and their accuracy.

Table 3: Comparative Analysis

Author	Year	Technique	Accuracy
Rasool and Amir [30]	2024	Hybrid CNN_LSTM model	99%
SALMAN et al.[34]	2022	Yolo general purpose object detection algorithm	97%
Proposed model	2024	Neuro-Fuzzy system	100%

5. Conclusion and Future Scope

The research highlights the significance of soft computing technology, particularly in the area of image recognition. The development and implementation of a new algorithm that combines neuro-fuzzy logic have demonstrated the effectiveness of utilizing these techniques to achieve exceptional performance metrics. This model demonstrates the strength and flexibility provided by soft computing methods. These results not only validate this approach's efficacy but also highlight its potential for addressing the demands of advanced image recognition applications. This study demonstrates the powerful impact of soft computing, combining neural networks and fuzzy logic to improve predictive performance and reliability. Thus, the integration of these techniques represents a promising possibility for advancing the field of image recognition and meeting the evolving needs of diverse applications.

In the future, the research could focus on developing hybrid models that combine neural networks, evolutionary algorithms, and fuzzy systems to improve accuracy and efficiency. Additionally, the application of these techniques to real-time image recognition tasks holds significant potential, particularly in domains requiring high precision and adaptability. For example, in medical imaging, these advanced models could improve diagnostic accuracy and treatment planning. Similarly, autonomous vehicles could enhance object detection and navigation capabilities, contributing to safer and more reliable self-driving systems. The continuous development and integration of these techniques are expected to drive significant progress in image recognition and other related fields.

References

[1] Perera, Yasith S., D. A. A. C. Ratnaweera, Chamila H. Dasanayaka, and Chamil Abeykoon. "The role of artificial intelligence-driven soft sensors in advanced sustainable process industries: A critical review." Engineering Applications of Artificial Intelligence 121 (2023): 105988.

[2] Dymova, Ludmila, Krzysztof Kaczmarek, Pavel Sevastjanov, and Joanna Kulawik. "A fuzzy multiple criteria decision wasapproaching with a complete, user-friendly computer implementation." *Entropy* 23, no. 2 (2021): 203.

[3] Elyan, Eyad, PattaramonVuttipittayamongkol, Pamela Johnston, Kyle Martin, Kyle McPherson, Chrisina Jayne, and Mostafa Kamal Sarker. "Computer vision and machine learning for medical image analysis: recent advances, challenges, and way forward." *Artificial Intelligence Surgery* 2 (2022).

[4] Khan, Rijwan, Santosh Kumar, Niharika Dhingra, and Neha Bhati. "The use of different image recognition techniques in food safety: a study." *Journal of Food Quality* 2021, no. 1 (2021): 7223164.

[5] Abd Elaziz, Mohamed, Abdelghani Dahou, Laith Abualigah, Liyang Yu, Mohammad Alshinwan, Ahmad M. Khasawneh, and Songfeng Lu. "Advanced metaheuristic optimization techniques in applications of deep neural networks: a review." *Neural Computing and Applications* (2021): 1-21.

[6] Legast, Magali, and Axel Legay. "Rule-based expert system for energy optimization: Detection and identification of relationships between rules in a knowledge base." PhD diss., Master’s thesis, UCLouvain, 2021.

[7] Casal-Guisande, Manuel, Alberto Comesaña-Campos, Alejandro Pereira, José-Benito Bouza-Rodríguez, and Jorge Cerqueiro-Pequeño. "A decision-making methodology based on expert systems applied to machining tools condition monitoring." *Mathematics* 10, no. 3 (2022): 520.

[8] Panigrahi, Sweta, and Surya Narayana Raju Undi. "Scale-invariant histogram of oriented gradients: a novel approach for pedestriandetection in multiresolution image

dataset." Turkish Journal of Electrical Engineering and Computer Sciences 29, no. 7 (2021): 3053-3073.

[9] Chen, Lin, Franz Rottensteiner, and Christian Heipke. "Feature detection and description for image matching: from hand-crafted design to deep learning." Geo-spatial Information Science 24, no. 1 (2021): 58-74.

[10] Khani, Masoud. "Medical image segmentation using machine learning." PhD diss., The University of Wisconsin-Milwaukee, 2021.

[11] Touvron, Hugo, Piotr Bojanowski, Mathilde Caron, Matthieu Cord, Alaaeldin El-Nouby, Edouard Grave, Gautier Izacard et al. "Resmlp: Feedforward networks for image classification with data-efficient training." IEEE Transactions on Pattern Analysis and Machine Intelligence 45, no. 4 (2022): 5314-5321.

[12] Zhu, Zheng, Guan Huang, Jiankang Deng, Yun Ye, Junjie Huang, Xinze Chen, Jiagang Zhu et al. "Webface260m: A benchmark unveiling the power of million-scale deep face recognition." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 10492-10502. 2021.

[13] Santos, Claudio Filipi Gonçalves Dos, and João Paulo Papa. "Avoiding overfitting: A survey on regularization methods for convolutional neural networks." ACM Computing Surveys (CSUR) 54, no. 10s (2022): 1-25.

[14] Ameryan, Mahya, and Lambert Schomaker. "A limited-size ensemble of homogeneous CNN/LSTMs for high-performance word classification." Neural Computing and Applications 33, no. 14 (2021): 8615-8634.

[15] Bronskill, John, Daniela Massiceti, Massimiliano Patacchiola, Katja Hofmann, Sebastian Nowozin, and Richard Turner. "Memory efficient meta-learning with large images." Advances in neural information processing systems 34 (2021): 24327-24339.

[16] Zhou, Fan, Chengtai Cao, Ting Zhong, and Ji Geng. "Learning meta-knowledge for few-shot image emotion recognition." Expert Systems with Applications 168 (2021): 114274.

[17] Panigrahi, Sweta, and Surya Narayana Raju Undi. "Scale-invariant histogram of oriented gradients: a novel approach for pedestriandetection in multiresolution image dataset." Turkish Journal of Electrical Engineering and Computer Sciences 29, no. 7 (2021): 3053-3073.

[18] Chen, Lin, Franz Rottensteiner, and Christian Heipke. "Feature detection and description for image matching: from hand-crafted design to deep learning." Geo-spatial Information Science 24, no. 1 (2021): 58-74.

[19] Khani, Masoud. "Medical image segmentation using machine learning." PhD diss., The University of Wisconsin-Milwaukee, 2021.

[20] Dinçer, Hasan, Serkan Eti, Tamer Aksoy, Serhat Yüksel, Ümit Hacioğlu, Alexey Mikhaylov, and S. M. Muyeen. "Analysis of environmental impact for material production investments using a novel soft computing methodology." IEEE Access 11 (2023): 37987-38001.

[21] Dumitrescu, Catalin, Petrica Ciotirnae, and Constantin Vizitiu. "Fuzzy logic for intelligent control system using soft computing applications." Sensors 21, no. 8 (2021): 2617.

[22] Ayadi, Rami, Rasha M. Abd El-Aziz, Ahmed I. Taloba, Hanan Aljuaid, Nadir O. Hamed, and Moaiad A. Khder. "Deep learning–based soft sensors for improving the flexibility for automation of industry." Wireless Communications and Mobile Computing 2022, no. 1 (2022): 5450473.

[23] Adhikari, Surabhi, Surendrabikram Thapa, and Awishkar Ghimire. "Soft computing techniques for medical diagnosis, prognosis and treatment." In Advanced Soft Computing Techniques in Data Science, IoT and Cloud Computing, pp. 371-399. Cham: Springer International Publishing, 2021

[24] Ishaque, Mohammed, Md Gapar, Md Johar, Ali Khatibi, and Muhammed Yamin. "A novel hybrid technique using fuzzy logic, neural networks and genetic algorithm for intrusion detection system." Measurement: Sensors 30 (2023): 100933.

[25] Genzel, Martin, Jan Macdonald, and Maximilian März. "Solving inverse problems with deep neural networks–robustness included." IEEE Transactions on pattern analysis and machine intelligence 45, no. 1 (2022): 1119-1134.

[26] Thakur, Amey, Karan Dhiman, and Mayuresh Phansikar. "Neuro-fuzzy: artificial neural networks & fuzzy logic." Int. J. Res. Appl. Sci. Eng. Technol 9 (2021): 128-135.

[27] Zohuri, Bahman, Seyed Kamal Mousavi Balgehshiri, and Mohammad Amin Imani. "Harmony in Complexity Exploring the Synergy of Fuzzy Logic, Group Theory, and Artificial Intelligence." Nov Joun of Appl Sci Res, 1 (2), 01 7 (2024).

[28] Mao, Yimin, YicouldLi, Fei Teng, Arkan KS Sabonchi, Mohammad Azarafza, and Maosheng Zhang. "Utilizing Hybrid Machine Learning and Soft Computing Techniques for Landslide Susceptibility Mapping in a Drainage Basin." Water 16, no. 3 (2024): 380.

[29] Talaat, Fatma M., Zainab H. Ali, Reham R. Mostafa, and Nora El-Rashidy. "Real-time facial emotion recognition model based on kernel autoencoder and convolutional neural network for autism children." Soft Computing (2024): 1-14.

[30] Rasool, Zahraa Haimeed, and Maha Adham Abdel Amir. "Comprehensive Image Classification using Hybrid CNN-LSTM Model with Advanced Feature Extraction on Coco Dataset." Mustansiriyah Journal of Pure and Applied Sciences 2, no. 2 (2024): 28-47.

[31] Singh, Sumit Kumar, Vahid Abolghasemi, and Mohammad Hossein Anisi. "Fuzzy logic with deep learning for detection of skin cancer." Applied Sciences 13, no. 15 (2023): 8927.

[32] Khan, Abdul Hannan, Sagheer Abbas, Muhammad Adnan Khan, Umer Farooq, Wasim Ahmad Khan, Shahan Yamin Siddiqui, and Aiesha Ahmad. "Intelligent model for brain tumour identification using deep learning." Applied Computational Intelligence and Soft Computing 2022 (2022): 1-10.

[33] Goyal, Shimpy, and Rajiv Singh. "Detection and classification of lung diseases for pneumonia and COVID-19 using machine and deep learning techniques." Journal of Ambient Intelligence and Humanized Computing 14, no. 4 (2023): 3239-3259.

[34] Salman, Mehmet Emin, Gözde Çakirsoy Çakar, Jahongir Azimjonov, Mustafa Kösem, and İsmail HakkıCedimoğlu. "Automated prostate cancer grading and diagnosis system using deep learning-based Yolo object detection algorithm." Expert Systems with Applications 201 (2022): 117148.

[35] Al-Akhras, Mousa, Mohammed Alawairdhi, and Mohamed Habib. "Using soft computing techniques to diagnose Glaucoma disease." Journal of Infection and Public Health 14, no. 1 (2021): 109-116.

[36] Narendra, V. G., and Ancilla J. Pinto. "Defects detection in fruits and vegetables using image processing and soft computing techniques." In Proceedings of 6th International Conference on Harmony Search, Soft Computing and Applications: ICHSA 2020, Istanbul, pp. 325-337. Springer Singapore, 2021.

[37] https://cocodataset.org/#home

[38] https://www.v7labs.com/blog/coco-dataset-guide

[39] Zou, Zilong, Jie Yang, Vasileios Megalooikonomou, Rachid Jennane, Erkang Cheng, and Haibin Ling. "Trabecular bone texture classification using wavelet leaders." In Medical Imaging 2016: Biomedical Applications in Molecular, Structural, and Functional Imaging, vol. 9788, pp. 107-112. SPIE, 2016.

[40] Chaki, Jyotismita, and Nilanjan Dey. Texture feature extraction techniques for image recognition. Springer Singapore, 2020.

[41] Labrín, Caterina, and Francisco Urdinez. "Principal component analysis." In R for Political Data Science, pp. 375-393. Chapman and Hall/CRC, 2020

[42] https://www.statistixl.com/features/principal-components/

[43] Jo, Han-Shin, Chanshin Park, Eunhyoung Lee, Haing Kun Choi, and Jaedon Park. "Path loss prediction based on machine learning techniques: Principal component analysis, artificial neural network, and Gaussian process." Sensors 20, no. 7 (2020): 1927

[44] Božanić, Darko I., Rade V. Slavković, and Samed M. Karović. "Model of fuzzy logic application to the assessment of risk in overcoming the water obstacles during an army defensive operation." Vojnodelo 67, no. 4 (2015): 240-260.

[45] Pamučar, Dragan. "Selection of a course of action by Obstacle Employment Group based on a fuzzy logic system." Yugoslav Journal of Operations Research 26, no. 1 (2016).

[46] Bozanic, Darko, Duško Tešić, Dragan Marinković, and Aleksandar Milić. "Modeling of neuro-fuzzy system as a support in decision-making processes." Reports in Mechanical Engineering 2, no. 1 (2021): 222-234.

[47] Božanić, Darko I., and Dragan S. Pamučar. "Making of fuzzy logic system rules base for decision making support by aggregation of weights of rules premises." Tehnika 69, no. 1 (2014): 129-138.

Citation: Mandlik G. G, Lokhande S. N. (2025). Optimizing Image Recognition Through a Novel Soft Computing Algorithm. International Journal of Computer Engineering and Technology (IJCET), 16(1), 4129-4156.

Abstract Link: https://iaeme.com/Home/article_id/IJCET_16_01_281

Article Link:
https://iaeme.com/MasterAdmin/Journal_uploads/IJCET/VOLUME_16_ISSUE_1/IJCET_16_01_281.pdf

✉ **editor@iaeme.com**