International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Fruit Detection and Classification application Based on Machine Learning Techniques Framework

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Submitted: 28/01/2024 **Revised**: 08/03/2024 **Accepted**: 13/03/2024

Abstract: The paper presents a comprehensive framework for accurately and efficiently recognizing fruits and vegetables, addressing the challenge systematically. Various feature descriptors based on color and texture are examined. These descriptors capture different aspects of the fruits and vegetables, aiding in their accurate recognition. Otsu's thresholding is utilized for background subtraction, a crucial step to isolate the fruits and vegetables from their surroundings. All segmented images are used in this phase to extract relevant features. This step likely involves removing texture and color information, utilizing the chosen descriptors. The extracted features are used to train and classify fruits and vegetables. Two classifiers, C4.5 and KNN, are employed for this purpose. Various performance metrics such as Classification Accuracy (CA), precision, recall, F-measure, Matthews Correlation Coefficient (MCC), Precision-Recall Curve (PRC), and False Positive Rate (FPR) are used to evaluate the proposed system's performance for the recognition problem. C4.5 classifier achieves a CA value of 92.43%, indicating high accuracy in classifying fruits and vegetables. KNN classifier performs a slightly lower CA value of 89.58% but still demonstrates significant accuracy in classification.

Keywords: *Detection, fruits, vegetables, descriptor, Deep Learning. Machine Learning*

1. Introduction

India's horticulture sector boasts remarkable diversity due to its versatile environmental conditions. Fruits and vegetables dominate this sector, comprising 90% of the total production. Apart from these, other categories include flowers, aromatic plants, crops, and spices. Among fruits and vegetables, the production stands at 314.65 million tons. In vegetable production, Uttar Pradesh leads with 26.4 million tons, followed closely by West Bengal with 25.5 million tons, contributing 30% to the total vegetable production in India. Andhra Pradesh tops 120.98 lakh tons in fruits, trailed by Maharashtra with 103.78 lakh tons, making up 24% of the national fruit production. India's export of fruits and vegetables is 161 USD million, ranking 14th globally [1].

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The appearance of fruits and vegetables is crucial in determining their market value and consumer preference. Traditionally, manual inspections by experienced individuals have been the norm for quality assessment, but this method can be inconsistent, affecting the selection of produce [2]. In today's digital era, many consumers purchase fruits and vegetables online. Supermarkets have also begun implementing recognition systems using hardware components and barcodes. However, one major limitation of such systems is their static nature. Barcode-based systems may fail to recognize the quality of fruits and vegetables accurately. A practical and automated recognition system is needed to enhance accuracy and meet consumer demands. Such a system could significantly improve the efficiency of the selection process and subsequently increase revenue for those involved in producing fruits and vegetables. Integrating machine learning into the recognition system could further enhance its performance. By leveraging machine learning algorithms, the system could learn from data patterns and continuously improve its accuracy in identifying and assessing the quality of fruits and vegetables [3].

The proposed fruit and vegetable image recognition framework combines color and texture features to classify images into different classes. Color spaces like RGB, CMH, CCV, and CDH and texture descriptors like LBP, CSLBP, and SEH are utilized [4-5]. In the recognition process, these descriptors extract features from the images. The extracted features are then used for classification, employing algorithms such as C4.5 decision trees and k-nearest neighbor (KNN). The proportion of correctly classified instances out of the total cases. The ratio of correctly classified positive cases to the real actual positive instances. The ratio of correctly classified positive instances to the confirmed cases is positive. A correlation coefficient is used in classification to consider true and false positives and negatives. By evaluating the classification results using these performance metrics, the effectiveness of the recognition system can be assessed comprehensively, providing insights into its accuracy, robustness, and suitability for practical deployment.

One of the critical challenges is the necessity of a comprehensive dataset to evaluate the system thoroughly. A robust dataset is crucial as it forms the bedrock for training an effective recognition system. The availability of sufficient data significantly simplifies introducing a recognition system. Extensive literature surveys of previous research work are essential to address these challenges. These surveys provide valuable insights into the existing methodologies, techniques, and challenges in fruit and vegetable image recognition. Based on this knowledge, a framework that integrates suitable descriptors, classification algorithms, and performance evaluation metrics can be developed. The proposed framework should be presented systematically, clearly delineating the methodology, experimental setup, and results. A crucial aspect of this framework is the comparative analysis of the results obtained from different techniques. This analysis aids in understanding the strengths and weaknesses of each method, thereby guiding the selection process.

2. Literature Survey

In this section, we will delve into an extensive literature survey of previous work conducted by numerous researchers in image recognition and classification. The earliest endeavors in image recognition and classification were made by several authors [5-6]. They utilized color and texture descriptors to extract features from the images. All these features were employed in training and classification using a KNN classifier. The proposed system achieved a remarkable 95% accuracy rate. However, one notable limitation is that the dataset used for experimentation needs to be updated. Consequently, the system may not fully leverage recent developments in datasets related to fruits and vegetables.

Fruits and vegetables are crucial in sustaining life, providing essential resources like food, fiber, shelter, medicine, and fuel. However, they face various challenges, particularly maintaining their health against infections. If not properly diagnosed, these infections can adversely affect the quality and quantity of plant products, exacerbating economic impacts on countries reliant on agriculture. Using fungicides and bactericides to combat plant diseases has significant implications for agricultural ecology. Misdiagnosis by farmers can lead to inefficient treatment methods, further damaging the plants and potentially causing environmental harm through the excessive use of chemical inputs [7]. To address these challenges, there's a growing need for accurate and rapid disease categorization methods in the agricultural ecosystem. Advances in disease detection technologies, such as image processing and machine learning-based models, offer promising solutions. By leveraging these technologies, early diagnosis of infections on plant leaves, like dragon leaves, can be achieved, enabling timely intervention to mitigate the spread of diseases. Early detection and appropriate management of plant infections reduce the risk of output loss and processing expenses and minimize the negative environmental impacts associated with chemical inputs, such as soil and water pollution. Therefore, enhancing systems for early illness categorization using advanced technologies is essential for sustaining agricultural productivity and environmental health.

The author [8] utilized the same dataset for their experiment, using K-means clustering to subtract the background of fruits and vegetables. The segmented images were then subjected to feature extraction. They extracted feature vectors using colour descriptors such as GCH, CCV, and CDH and texture descriptors such as SEH, LBP, and CSLBP. These features were used for training and classification using a multi-class support vector machine. In another paper by the author [9], focusing on the same experimental dataset, they analysed the mean (μ) and standard deviation (σ) of all classes of fruits and vegetables. They found that the fused descriptor CCV + LTP produced the highest mean accuracy rate at 90.6%, while the lowest was 3.8% by CCV + CLBP. However, one drawback they identified was that CDH + SEH produced a lower mean accuracy rate, and CDH + SEH + CSLBP showed the highest standard deviation, indicating poorer performance than other methods. These findings highlight the importance of carefully selecting and combining descriptors to achieve optimal performance in fruit and vegetable classification systems.

The author [10] introduced a novel approach to the recognition of fruits and vegetables. In their study, they fused multiple features with a classifier. The dataset they utilized consisted of 15 different classes of fruits and vegetables for their experiments. The feature descriptors they employed were primarily related to color and texture. Their results demonstrated that the proposed system reduced classification errors by up to 15%. They also combined feature descriptors to handle more complex images with variability in number, illumination, and poses. However, one drawback they noted is that the system may need help to achieve a reasonable accuracy rate when combining weak features with a high-accuracy classifier. This emphasizes the importance of carefully selecting and balancing features when designing a classification system. The author [11-12] introduced a framework for recognizing particular images belonging to a set of images per class. This approach, known as bag-of-features techniques, has shown promising results for recognition problems, as demonstrated by [13-14]. The author [15] also conducted experiments using different categories of fruits and vegetables, achieving a reasonable accuracy rate of 86%. Additionally, the author [16] proposed an exciting method for shape matching.

The author [17-18] recently presented a fruit recognition and classification framework. Their work focused on classifying apples into healthy and defective categories using SVM, MLP, and KNN classifiers. The results indicated that the SVM classifier achieved the highest accuracy rate, with 92.5% and 89.2% values for both classes, respectively. The MLP classifier followed with recognition rates of 90.0% and 86.5%. Finally, the KNN classifier produced lower accuracy rates, with 87.5% and 85.8% values for healthy and defective classes. They provided a detailed description of the features of a dataset containing date fruits. The author's [19] study introduces a hybrid machine-learning technique for diagnosing plant bacterial and fungal diseases. Their research utilized a dataset comprising 500 samples categorized into three classes: fungal, bacterial, and healthy. The results indicated promising performance for the hybrid models. Specifically, the CNN-KNN hybrid achieved an accuracy of 92.4%, while the CNN-RF hybrid achieved 87.4% accuracy. Additionally, the CNN-SGD hybrid outperformed the others with an accuracy of 93.6%. These findings demonstrate the efficacy of combining convolutional neural networks with traditional machine learning algorithms for diagnosing plant diseases. Such hybrid approaches leverage the strengths of both deep learning and classical machine learning techniques, resulting in improved accuracy and robustness in disease classification tasks.

3. Proposed Framework for Recognition of Fruits and Vegetables:

3.1: Background subtraction:

In this paper, we propose a framework for segmenting fruit and vegetable images by employing Otsu's algorithm for background subtraction. Otsu's algorithm is widely utilized in various segmentation processes and is particularly effective under occlusion, cropping, noisy, and blurred images. Our proposed approach was experimented with fruit and vegetable images obtained locally. The experimental results confirm that Otsu's threshold-based technique can accurately extract fruit and vegetable items. To evaluate the performance of our proposed method, we utilized a dataset containing 20 different categories of fruits and vegetables. This framework addresses the crucial and challenging task of accurately segmenting fruit and vegetable images, which is fundamental in computer vision applications. By leveraging Otsu's algorithm, our method demonstrates robustness and effectiveness in various image conditions, ultimately contributing to improved fruit and vegetable segmentation accuracy.

3.2 Feature Extraction:

The statement highlights the challenges in selecting appropriate extraction methods and descriptor selection strategies for categorizing fruits and vegetables. Despite the absence of clear guidelines, the study focuses on extracting capabilities that have shown promise in addressing these issues. For fruit and vegetable categorization, the study utilizes a combination of color and texture features to evaluate accuracy and performance. Specifically, color features such as RGB, CCV, CDH, and CMH are employed [20-21]. Texture features LBP, CSLBP, and SEH are also utilized [22]. By incorporating these features into the categorization process, the study aims to enhance the accuracy and effectiveness of fruit and vegetable recognition systems. This approach recognizes the importance of color and texture characteristics in distinguishing different types of fruits and vegetables, contributing to advancements in automated classification methods within the agricultural domain.

3.2.1 RGB histogram:

The RGB histogram is a composite representation of three 1D histograms based on the Red (R), Green (G), and Blue (B) channels of the RGB colour space. In the normalized RGB color model, the chromaticity components r and g describe the color information in the image. In this model, the sum of r, g, and b will always equal one, expressed as $r + g + b = 1$. This normalization ensures that the colour components represent proportions of the total colour intensity, facilitating comparisons between images regardless of brightness.

3.2.2 Color difference histogram:

The Color Difference Histograms (CDHs) feature descriptor is designed by considering the color differences of neighboring pixels at a specific distance [23]. CDH is distinctive in that it measures the perceptually uniform color difference between points under different backgrounds, considering colors and edge orientations in the Lab* color space. This descriptor focuses on color, edge orientation, and perceptually uniform color variations. It encodes color, orientation, and perceptually uniform color differences through feature representation like the human visual system. By considering these factors, CDH captures essential information about color variations and spatial relationships in the image, making it an effective tool for image analysis and recognition tasks.

*3.2.3 C*olor coherence vector:

This method defines color coherence as the degree to which image pixels of a particular color contribute to a large area with homogeneous color [24]. These are called coherent regions, where coherent pixels belong to large contiguous areas while incoherent pixels do not. By distinguishing between cohesive and incoherent pixels and computing separate histograms for each, CCV provides a robust representation of the image's color coherence structure. This approach enables practical analysis and image classification based on color coherence characteristics.

3.2.4 Local binary pattern:

The central concept of Local Binary Patterns [25], is to tell the texture of grayscale images by extracting their local spatial structure or by capturing the sign of the difference between neighboring pixels and the central pixel. In essence, LBP calculates a binary code for each pixel based on comparing intensity values between the central pixel and its surrounding neighbors. This binary code represents the local texture pattern of the image. After computing the LBP code for each pixel in the picture, a histogram of these LBP codes is generated. This histogram represents the distribution of different texture patterns across the image.

3.2.5 Centre-symmetric local binary pattern:

To address the long histograms produced by the traditional Local Binary Patterns operator, we modified the scheme to compare pixels within the neighborhood differently. Instead of comparing each pixel with the central pixel, we compared centrally symmetric pairs of pixels. For example, in the case of 8 neighbors, traditional LBP produces 256 (2^8) unique binary patterns, whereas with the centrally symmetric Local Binary Pattern (CS-LBP), this number is reduced to only 16 (2^4). This reduction in the number of patterns simplifies the representation of texture features while still capturing crucial spatial information [26].

3.2.5 Structure element histogram:

When the pixel count of an image changes due to scaling, the values computed by the Structure Element Histogram (SEH) would also change accordingly [27]. This can lead to dissimilarities between images, even if they represent the same content but at different scales. Normalization is a suitable approach to address this issue. Normalizing the SEH values ensures that the histograms represent the relative distribution of structure elements within the image rather than absolute counts. This normalization process allows us to compare images effectively, even when scaled differently. By ensuring that the proportion of pixels in each structure element remains constant across different scales, we can achieve more robust and consistent comparisons between images, regardless of their size or resolution.

3.3 Training and classification:

Once the features are extracted from the training images, classifiers such as C4.5 and KNN are trained using these feature vectors [28-29]. These trained classifiers are then utilized to categorize the test images into one of the classes of fruits and vegetables based on their feature vectors generated using the same descriptor employed for feature extraction. It's important to note that different classifiers employ different strategies for training, but fundamentally, they all perform optimization operations to separate the training data into distinct categories. It's also worth mentioning that KNN classifiers can be used for continuous value inputs, unlike Decision Trees, which are suitable for both constant and categorical inputs. This flexibility allows for the adaptation of classifiers to different types of data, enhancing the overall effectiveness of the classification process.

3.3.1 C4.5 classifier:

The decision tree classifier operates by classifying a given data point starting from the top and moving down to reach a leaf node based on approximating a discrete-valued target feature. Learning in decision trees is based on constructing a decision tree that represents the training instances provided to the ID3 algorithm. The decision tree is formed based on a set of training examples. These trees can be implemented as a set of if-then rules, which improve decision-making capabilities. The tree's construction follows a top-down approach, beginning with the formation of the root node. At each node, the best attribute for classification is selected as the test attribute based on the highest information gain at that node. Information gain is the reduction in entropy resulting from splitting the instances based on attribute values.

3.3.2 KNN classifier:

When a new, unlabeled data point needs to be classified, the KNN algorithm identifies the k nearest neighbors to the new data point in the feature space. The number k is a hyperparameter that must be specified in advance. Once the k nearest neighbors is identified, the algorithm assigns the new data point to the most common class among its k neighbors. This is typically done using a majority voting scheme. The distance between data points is typically calculated using metrics such as Euclidean distance, Manhattan distance, or Minkowski distance. The choice of the parameter k can significantly impact the performance of the KNN classifier. A small value of k may result in a noisy classification, while a significant value of k may result in a biased classification. The optimal value of k is often determined through cross-validation. However, it can be computationally expensive, especially for large datasets, as it requires storing and comparing distances with all training instances. Additionally, it may perform poorly in high-dimensional feature spaces or when the data is imbalanced.

4. Experiment and Results:

In this section, we first discuss the dataset of fruits and vegetables that was utilized in our study. We describe the preparation of this dataset, including any preprocessing steps that were applied to the images. Next, we compare various color and texture feature descriptors to extract meaningful features from the pictures of fruits and vegetables. These descriptors may include but are not limited to RGB histograms, color coherence vectors (CCV), color difference histograms (CDH), color moment histograms (CMH), local binary patterns (LBP), and structure element histograms (SEH). Once the features are extracted using different descriptors, we evaluate the recognition accuracy of the fruits and vegetables. This evaluation involves training and testing various classifiers, such as C4.5 decision trees, K-nearest neighbors (KNN), support vector machines (SVM), or multi-layer perceptron's (MLP), using the extracted features as input. By comparing the performance of different feature descriptors and classifiers, we can determine which combination yields the highest recognition accuracy for the given dataset of fruits and vegetables. This analysis helps identify the most effective image recognition and classification techniques in this domain.

Fig 2: Dataset used to have 20 different categories of fruits and vegetables

To analyses the recognition accuracy of the proposed system, we conducted a comparative study using various feature descriptors. During the evaluation process, we utilized a dataset containing images of fruits and vegetables, with multiple photos for each category for training purposes. By evaluating the proposed system using these performance metrics, we can gain insights into its effectiveness in accurately recognizing and classifying fruits and vegetables based on their image features. This comprehensive analysis allows us to identify the strengths and weaknesses of different feature descriptors and assess the system's overall performance. Based on the information provided, the system achieved high accuracy rates with both the C4.5 and KNN classifiers, indicating good overall recognition performance. However, there are some trade-offs to consider: The recall rate, which measures the ability to recognize fault-free samples, is lower than the accuracy rate. This suggests that while the system performs well overall, it may miss some fault-free samples. The low false positive rate indicates that the system often needs to misclassify fault-free sores, which is a positive aspect. The precision values also suggest that the fault-free sample recognition rate is lower than the overall accuracy rate.

Table 1: Results of metric wise performance over C4.5

Accuracy	92.43
Recall	77.4
Precision	76.43
F-measure	75.55
MCC	72.76
PRC	73.42
FPR	1.43

Table 2: Results of metric wise performance over KNN

Accuracy	89.58
Recall	65.43
Precision	67.83
F-measure	72.55
MCC	68.12
PRC	64.76
FPR	3.54

5. Conclusion

The paper presents a novel framework for fruit and vegetable recognition, focusing on three main phases: segmentation, feature extraction, and training/classification. One significant contribution is the creation of a dataset comprising 20 different categories of fruits and vegetables. In the segmentation phase, the background of the images is subtracted using Otsu's thresholding method. Then, state-of-the-art features are extracted from the segmented images, which are subsequently used for training and classification. Various performance metrics are employed to evaluate the proposed framework, including accuracy, recall, false positive rate, and precision. The results indicate that the C4.5 classifier outperforms the KNN classifier across all performance metrics, demonstrating its effectiveness and superior performance in this context. Overall, the paper presents a comprehensive framework for fruit and vegetable recognition, leveraging advanced techniques in image processing and machine learning to achieve accurate classification results. The comparison between classifiers provides valuable insights into the effectiveness of different approaches in this domain.

Reference:

[1] Abbas, Z. K., & Al-Ani, A. A. (2022). Anomaly detection in surveillance videos based on H265 and deep learning. International Journal of Advanced Technology and Engineering Exploration, 9(92), 910–922. https://doi.org/10.19101/IJATEE.2021.875907

[2] Abdullah, F., Javeed, M., & Jalal, A. (2021). Crowd Anomaly Detection in Public Surveillance via Spatio-temporal Descriptors and Zero-Shot Classifier. 4th International Conference on Innovative Computing, ICIC 2021, November.

[3] Shivendra, Kasa Chiranjeevi, and Mukesh Kumar Tripathi. "Detection of Fruits Image Applying Decision Tree Classifier Techniques." In Computational Intelligence and Data Analytics: Proceedings of ICCIDA 2022, pp. 127-139. Singapore: Springer Nature Singapore, 2022.

[4] Bedekar, U., & Bhatia, G. (2022). A Novel Approach to Recommend Skincare Products Using Text Analysis of Product Reviews. In Lecture Notes in Networks and Systems (Vol. 191, Issue Ictcs). https://doi.org/10.1007/978-981-16-0739-4_24

[5] Tripathi, Mukesh Kumar, and Shivendra. "Neutroscophic approach based intelligent system for automatic mango detection." Multimedia Tools and Applications (2023): 1-23.

[6] Doshi, K., & Yilmaz, Y. (2020). Continual learning for anomaly detection in surveillance videos. IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 2020-June, 1025–1034.

[7] Franklin, R. J., Mohana, & Dabbagol, V. (2020). Anomaly Detection in Videos for Video Surveillance Applications using Neural Networks. Proceedings of the 4th International Conference on Inventive Systems and Control, ICISC 2020, January 2020, 632–637. https://doi.org/10.1109/ICISC47916.2020.9171212

[8] Tripathi, Mukesh Kumar, Praveen Kumar Reddy, and Madugundu Neelakantappa. "Identification of mango variety using near infrared spectroscopy." Indonesian Journal of Electrical Engineering and Computer Science 31, no. 3 (2023): 1776-1783.

[9] Gong, M., Zeng, H., Xie, Y., Li, H., & Tang, Z. (2020). Local distinguishability aggrandizing network for human anomaly detection. Neural Networks, 122, 364–373.

[10] Tripathi, Mukesh Kumar, Dhananjay Maktedar, D. N. Vasundhara, CH VKNSN Moorthy, and Preeti Patil. "Residual Life Assessment (RLA) Analysis of Apple Disease Based on Multimodal Deep Learning Model." International Journal of Intelligent Systems and Applications in Engineering 11, no. 3 (2023): 1042-1050.

[11] Lindemann, B., Maschler, B., Sahlab, N., & Weyrich, M. (2021). A Survey on Anomaly Detection for Technical Systems using LSTM Networks. Computers in Industry, 131, 1–14.

[12] Tripathi, Mukesh Kumar, M. Neelakantapp, Anant Nagesh Kaulage, Khan Vajid Nabilal, Sahebrao N. Patil, and Kalyan Devappa Bamane. "Breast Cancer Image Analysis and Classification Framework by Applying Machine Learning Techniques." International Journal of Intelligent Systems and Applications in Engineering 11, no. 3 (2023): 930-941.

[13] Santhosh, K. K., Dogra, D. P., & Roy, P. P. (2021). Anomaly Detection in Road Traffic Using Visual Surveillance: A Survey. ACM Computing Surveys, 53(6), 1–14.

[14] Tripathi, Mukesh Kumar, CH VKNSN Moorthy, Vidya A. Nemade, Jyotsna Vilas Barpute, and Sanjeev Kumar Angadi. "Mathematical Modelling and Implementation of NLP for Prediction of Election Results based on social media Twitter Engagement and Polls." International Journal of Intelligent Systems and Applications in Engineering 12, no. 14s (2024): 184-191.

[15] Shin, H., Na, K. I., Chang, J., & Uhm, T. (2022). Multimodal layer surveillance map based on anomaly detection using multi-agents for smart city security. ETRI Journal, 44(2), 183–193.

[16] Prasad, Tenneti Ram, Mukesh Kumar Tripathi , CH VKNSN Moorthy, S. B. Nandeeswar, and Manohar Koli. "Mathematical Modeling and Implementation of Multi-Scale Attention Feature Enhancement Network Algorithm for the Clarity of SEM and TEM Images." International Journal of Intelligent Systems and Applications in Engineering 12, no. 13s (2024): 230-238.

[17] Ullah, W., Ullah, A., Hussain, T., Khan, Z. A., & Baik, S. W. (2021). An efficient anomaly recognition framework using an attention residual lstm in surveillance videos. Sensors, 21(8).

[18] Yahaya, S. W., Lotfi, A., & Mahmud, M. (2021). Towards a data-driven adaptive anomaly detection

system for human activity. Pattern Recognition Letters, 145, 200–207.

[19] Tripathi, Mukesh Kumar, and Shivendra. "Improved deep belief network for estimating mango quality indices and grading: A computer vision-based neutrosophic approach." Network: Computation in Neural Systems (2024): 1-29.

[20] Dattatraya, K.N., Rao, K.R. “Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN”, Journal of King Saud University - Computer and Information Sciences, 2022, 34(3), pp. 716–726

[21] Tripathi, Mukesh Kumar, and M. Neelakantappa. "Election Results Prediction Using Twitter Data by Applying NLP." International Journal of Intelligent Systems and Applications in Engineering 12, no. 11s (2024): 537-546.

[22] Ramkumar, J., Karthikeyan, C., Vamsidhar, E., Dattatraya, K.N.,” Automated pill dispenser application based on IoT for patient medication”, EAI/Springer Innovations in Communication and Computing, 2020, pp. 231–253.

[23] Dattatraya, K.N., Raghava Rao, K., Satish Kumar, D., “Architectural analysis for lifetime maximization and energy efficiency in hybridized WSN model”, International Journal of Engineering and Technology(UAE), 2018, 7, pp. 494–501.

[24] Dattatraya, K.N., Ananthakumaran, S., “Energy and Trust Efficient Cluster Head Selection in Wireless Sensor Networks Under Meta-Heuristic Model”, Lecture Notes in Networks and Systems, 2022, 444, pp. 715–735.

[25] Moorthy, CH VKNSN, Mukesh kumar Tripathi, Nilesh Pandurang Bhosle, Vishnu Annarao Suryawanshi, Priyanka Amol Kadam, and Suvarna Abhimunyu Bahir. "Investigating Advanced and Innovative Non-Destructive Techniques to Grade the Quality of Mangifera Indica." International Journal of Intelligent Systems and Applications in Engineering 12, no. 1 (2024): 299-309.

[26] Zaheer, M. Z., Mahmood, A., Khan, M. H., Astrid, M., & Lee, S. I. (2021). An Anomaly Detection System via Moving Surveillance Robots with Human Collaboration. Proceedings of the IEEE International Conference on Computer Vision, 2021-October, 2595–2601.

[27] Tripathi, Mukesh Kumar, Sagi Hasini, Madupally Homamalini, and M. Neelakantappa. "Pothole Detection based on Machine Learning and Deep Learning Models." In 2023 International Conference on Advanced Computing Technologies and Applications (ICACTA), pp. 1-9. IEEE, 2023.

[28] Pallavi, Bhogadi Godha, E. Ravi Kumar, Ramesh Karnati, and Ravula Arun Kumar. "Lstm based named entity chunking and entity extraction." In 2022 First International Conference on Artificial Intelligence Trends and Pattern Recognition (ICAITPR), pp. 1-4. IEEE, 2022.

[29] Upadhyay, Shrikant, Mohit Kumar, Ashwani Kumar, Ramesh Karnati, Gouse Baig Mahommad, Sara A. Althubiti, Fayadh Alenezi, and Kemal Polat. "Feature extraction approach for speaker verification to support healthcare system using blockchain security for data privacy." Computational and Mathematical Methods in Medicine 2022 (2022).