IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 4 January 2024, accepted 7 February 2024, date of publication 12 February 2024, date of current version 23 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3365356

RESEARCH ARTICLE

A Novel Transfer Learning Approach for Detection of Pomegranates Growth Stages

AISHA NASEER[1], MADIHA AMJAD[1], ALI RAZA[2], KASHIF MUNIR[1], NAGWAN ABDEL SAMEE[3], AND MANAL ABDULLAH ALOHALI[4]

[1]Institute of Information Technology, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan
[2]Institute of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan
[3]Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[4]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

Corresponding authors: Madiha Amjad (madiha.amjad@kfueit.edu.pk) and Manal Abdullah Alohali (maalohaly@pnu.edu.sa)

This research was funded by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R330), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

ABSTRACT Pomegranates are nutrient-rich fruits renowned for their vibrant ruby-red seeds and antioxidant properties. With a rich history rooted in various cultures, pomegranates have gained widespread popularity for their distinct flavor and potential health benefits. Timely detection and understanding of the growth stages of pomegranates can facilitate optimized resource allocation, targeted interventions, and efficient crop management. Additionally, early detection contributes to maximizing crop yield, ensuring product quality, and mitigating potential risks such as diseases and pest infestations. The primary goal of the present study is the early detection of pomegranate growth stages using an efficient approach. We conducted our experiments using standard image data of the pomegranate growth stages, comprising 5857 files categorized into five classes: Bud, Early-Fruit, Flower, Mid-growth, and Ripe. We propose a transfer learning-based CRnet approach to capture spatial features from pomegranate images depicting the five stages of pomegranate growth. The extracted spatial features serve as inputs for the random forest method, resulting in the creation of a new probabilistic feature set. These new probabilistic features assist the proposed model in performing the detection of pomegranate growth stages. To evaluate performance, we implemented state-of-the-art image classification techniques, including a Convolutional Neural Network (CNN), K-Neighbors Classifier (KNC), Gaussian Naive Bayes (GNB), and Logistic Regression (LR). To ensure the accuracy of applied machine learning methods, we utilized a hyperparameter optimization approach and a k-fold-based cross-validation technique. Additionally, computational complexity is determined. Extensive analysis of research results shows that by using the proposed features, the random forest model outperformed state-of-the-art methods with a high accuracy of 98% in predicting pomegranate growth stages. Our proposed scheme has the potential for the timely detection of pomegranate growth stages, assisting farmers in maximizing crop yield and mitigating potential risks.

INDEX TERMS Pomegranates, pomegranate growth, machine learning, image processing, deep learning, transfer learning.

I. INTRODUCTION

Pomegranate is a fruit known for its rich nutrient content and abundance of antioxidants, offering a unique blend of sweet and tart flavours [1]. Widely cultivated in arid and

The associate editor coordinating the review of this manuscript and approving it for publication was Senthil Kumar.

semi-arid regions, the pomegranate stands as a significant fruit crop [2]. It possesses various distinctive qualities and is originally native to Iran and Afghanistan. In contemporary times, its cultivation has expanded to include regions across Africa, America, Australia, the Middle East, and Europe. Consumers enjoy pomegranates in various forms, including fresh fruit or processed into juice, jam, oil, or infusion [3]. It thrives in regions with an annual rainfall of approximately 40-50 cm.

Fruits are susceptible to diseases, and pomegranates, in particular, are highly prone to infections at various growth stages. The susceptibility of pomegranates to diseases poses a significant economic challenge for farmers [4], emphasizing the need to identify growth stages for proper plant monitoring and fulfilment of essential requirements. Acquiring knowledge about the various phases of pomegranate fruit development empowers cultivators to make well-informed choices regarding fertilization [5], pest control, and optimal harvest timing, thereby optimizing both fruit yield and quality. It is essential to acknowledge that the timing and features associated with each growth stage may vary depending on factors such as the pomegranate variety, environmental conditions, and cultivation circumstances.

Pomegranate cultivation holds significant importance in the agricultural sector due to the increasing demand for its nutritious fruit and its diverse applications in food, beverages, and cosmetics. However, the industry faces challenges related to diseases, alignment of quality evaluation with developmental phases, climate fluctuations, and soil nutrient management [6]. Farmers who struggle to accurately identify pomegranate growth stages may experience inefficiencies in resource allocation, impacting decisions regarding harvest timing and overall crop management [7]. The imprecision in detection could result in resource wastage, financial losses, and limitations on opportunities for advancing efficiency and sustainability in farming practices. To address these issues, advanced methods such as deep and transfer learning are being employed to tackle the challenges faced by farmers and explore potential avenues for simplifying and enhancing agricultural practices.

Neural networks have become indispensable tools in the recognition of agricultural images, particularly those depicting different growth stages [8]. Deep learning algorithms demonstrate the ability to comprehend intricate patterns and rich features within images, enabling them to discern subtle distinctions that may pose challenges to human perception [9], [10]. The training of deep learning models for growth stage image recognition typically involves extensive datasets comprising various growth stage images labelled with corresponding stage annotations. These models categorize fruit growth stage images based on their visual characteristics, providing agricultural professionals or farmers with a precise means of identifying stages and aligning plant management with the production stage. Transfer learning-based feature extraction is a promising approach to enhance the precision of growth stage image recognition. This approach employs pre-trained neural networks to identify optimal features from image data within the scope of tasks related to image classification [11]. In the context of images depicting plant growth stages, transfer learning facilitates the extraction of significant characteristics through a transfer process.

Our research study on predicting pomegranate growth stages contributes significantly in the following ways:

- A novel CRnet is proposed to capture spatial characteristics from pomegranate images depicting the five stages of pomegranate growth. The derived spatial features serve as inputs for the random forest technique, resulting in the creation of a probabilistic feature set that exhibits remarkable performance in predicting growth stages.
- To evaluate the performance of our proposed scheme in comparison to the state-of-the-art schemes, we implemented advanced classification methods, such as CNN, LR, GNB, and KNC.
- To enhance the precision of implemented machine and deep learning techniques, we utilize a strategy involving hyperparameter optimization and a cross-validation technique based on k-fold validation. Additionally, the computational complexity is determined. The proposed approach exhibited exceptional performance scores in comparison to existing state-of-the-art studies.

The rest of the paper is dissected into the following sections: Section II contains a comparative analysis conducted on relevant literature concerning the prediction of pomegranate growth stages using diverse stage images. The innovative methodology we propose is elucidated in Section III. Section IV comprises the experimental evaluations conducted in this study. The results and conclusions drawn from the study are presented in Section V.

II. RELATED WORK

The research in the active domain of employing transfer learning for feature engineering to forecast pomegranate growth stages, particularly using diverse stage images, remains a current focus. Recent investigations in automated orchard management have concentrated on constructing machine learning models to achieve precise and early identification of these growth stages of different fruits. However, there has been a scarcity of recent contributions in this area related to pomegranate. The majority of existing literature on the application of machine learning in pomegranate cultivation emphasizes disease detection using images [2], [4] and determining optimal parameters for yield maximization [6], [12], [13], [14], [15], [16]. Because there is limited existing literature on identifying the growth stages of pomegranates, we have explored machine learning methods used for recognizing growth stages in other crops, as detailed in this section.

We also provide an overview of related research, further subjected to comparative analysis in Table 1.

A most relevant scheme to our study is presented in [17], [18], and [19], where the authors employed a Yolo-v7 model to precisely locate pomegranates and assess their growth stages, contributing to improved efficiency in horticultural harvesting in orchards. The pomegranate imaging dataset, comprising 5857 images representing five growth stages (ripe, mid-growth, early-fruit, flower, and bud), was dissected into training, validation, and test sets with 4685, 585, and 587 images, respectively. Performance evaluation on the validation set, which included 1105 labels, resulted in recall, precision, mAP 0.5, and mAP 0.5:0.95 metrics of 0.873, 0.894, 0.939, and 0.822. Despite challenges associated with detecting small labels, their proposed approach demonstrated satisfactory results in performance metrics. The evaluation on a test dataset of 587 images and 1109 labels yielded recall, precision, mAP 0.5, and mAP 0.5:0.95 values of 0.888, 0.916, 0.943, and 0.824, respectively.

The proposition of utilizing Convolutional Neural Networks (CNN) for the grading of pomegranate fruit was introduced in [4]. The proposed system is an effective module for identifying diverse disorders in pomegranate fruit and determining the corresponding stage of illness. The research outlined a methodology for monitoring the growth stages of pomegranate fruit through the integration of image processing and machine learning approaches for disease detection. The approach involved analyzing color, shape, and texture data extracted from photos captured at different developmental phases to track the fruit's growth stages. The envisioned future scope involves the creation of user-friendly mobile applications for farmers, allowing them to capture pomegranate fruit images with their smartphones. The camera used in this project captured different stages of pomegranate fruit and classified them into infected and non-infected categories using machine learning algorithms and Python tools.

The research introduced the utilization of machine learning methodologies in pomegranate farming in [6], displaying encouraging outcomes that enhance multiple facets of the cultivation process. Through the application of machine learning algorithms, precise and efficient identification of soil nutrients, along with recommendations for solutions, has been achieved, empowering farmers to optimize nutrient management strategies. The heightened predictive accuracy in detecting nutrient deficiencies and recommending fertilizers for pomegranate farming resulted from systematic evaluations of various machine learning algorithms on a comprehensive dataset. In Pomegranate Quality Detection and Analysis, Convolutional Neural Networks (CNN) with VGG16 achieved an impressive accuracy of 97%, highlighting its potential to enhance fruit quality assessment in pomegranate cultivation. Overall, the study's findings underscore the significance of advanced algorithms in optimizing various aspects of pomegranate farming, spanning from nutrient management to disease detection and quality assessment.

The study [2] focused on the cultivation of two to three-year-old pomegranate trees (cv. Super Bhagwa) using a Randomized Block Design with 10 treatments and three replications each. The treatment T9, which involved 80% of the recommended dose of fertilizer (RDF) + Vermiwash + Cow urine through drip (1 liter/week), exhibited significantly higher yields in various parameters, such as fruit weight, fruit volume, number of fruit per plant, weight of fruit per plant, weight of aril per fruit, and peel weight per fruit. Throughout the experiment, the management of diseases and insect pests was effectively handled by both organic and inorganic fertilizers. The study suggests that organic sources alone can meet the nutritional requirements of pomegranates without compromising yield. Treatment T9, utilizing 80% of RDF along with Vermiwash and Cow urine through drip irrigation, emerged as the most effective method to enhance yield parameters for pomegranate fruits. This approach proved superior in terms of fruit weight, fruit volume, number of fruit per plant, weight of fruit per plant, weight of aril per fruit, and peel weight per fruit compared to other fertilizer treatments.

The research [12] investigated the economic implications of pomegranate research and extension activities on the agricultural economy in Maharashtra. It assessed the role of technology and input in overall productivity growth, focusing on both area expansion and productivity enhancement in pomegranate production. Through economic analysis, the study determined the economic value of the university-released pomegranate production technology, estimating it to be 98,616.07 per hectare in Maharashtra. The findings revealed that a one-rupee investment in pomegranate research yielded an additional income of 20.87, with an Internal Rate of Return (IRR) of 39.61%. The improved pomegranate varieties released by MPKV, Rahuri, contributed to gross and net economic benefits of 2,883 crores and 1,465 crores, respectively, for pomegranate growers in Maharashtra.

The research [13] explored the impact of plant growth regulators on various aspects of pomegranate cultivation, including growth and development, fruit yield and quality, propagation, and storage. It provided a concise overview of the positive effects observed in these areas. The utilization of plant growth regulators is a common practice in horticulture to enhance crop growth, and their application in pomegranate cultivation has demonstrated favorable outcomes in terms of increased fruit yield and improved quality. While traditional propagation methods like rooting hardwood cuttings are prevalent, the paper suggests that micropropagation techniques offer advantages such as producing genetically identical plants and facilitating rapid mass production of planting materials. Additionally, the paper notes the presence of two types of pomegranate flowers: hermaphrodite and male, without delving into specific methodologies employed.

The exploration of disease detection in pomegranates through image processing was introduced in [14]. The proposed system primarily aimed to create a detection system for diseases in pomegranate fruits, operating in two phases: Training and Testing. During the Training phase, a database was established with images of pomegranate fruits containing essential information about diseases. The Testing phase involves evaluating the algorithm using various input

TABLE 1. The summary and research limitations analysis of conducted literature for predicting growth stages through image detection.

Ref.	Year	Research Aim	Technique	Results
[4]	2023	Pomegranate fruit dataset that detects or identifies illnesses at various fruit stage	CNN	Did not specify the results.
[6]	2023	Utilization of machine learning methodologies in pomegranate farming	(CNN) with VGG16 , NPK , and RF .	VGG16-Based Convolutional Neural Networks Achieve 97% Accuracy.
[17]	2023	Pomegranate growth stages image dataset (5857).	Yolo-v7	Resulted in recall, precision, mAP@0.5, and mAP@0.5:0.95 metrics of 0.873, 0.894, 0.939, and 0.822.
[2]	2023	Influence of Organic and Inorganic Fertilizers on Pomegranate (Punica granatum L.) Yield in Precision Farming Systems.	Fertilizer Optimization: T9 Treatment with 80% RDF + Vermiwash + Cow Urine via Drip Irrigation (1 liter/week).	Optimizing Pomegranate Fruit Yields: T9 Identified as the Most Effective Enhancement Method.
[12]	2023	Economic Impact of Pomegranate Research and Extension: Enhancing Farm Economy.	Technology and Input Strategies for Growth in Area and Productivity.	MPKV Rahuri's Enhanced Pomegranate Varieties Drive Maharashtra Growers to Economic Gains of 2883 Crores.
[13]	2022	Impact of plant growth regulators on various aspects of pomegranate cultivation.	Micro propagation	Offer advantages such as producing genetically identical plants and facilitating rapid mass production of planting materials.
[19]	2021	A methodology for real-time monitoring to evaluate the developmental stage of strawberry fruits.	YOLOX and SDNet.	Color intensity Accuracy: 94.26%.
[14]	2020	The exploration of Disease Detection in Pomegranate through Image Processing.	Grabcut segmentation for Region of Interest (ROI) extraction.	The overall accuracy of disease detection was determined to be 85%.
[15]	2020	Influence of Macronutrient Levels on Reproductive Development in Two Pomegranate Varieties.	Container-Grown Trees: Evaluating Responses to Elevated N, P, and K Levels in Irrigation	Nutrient Influence on Andromonoecy: Higher Nitrogen and Phosphorus Levels Promote Hermaphroditic Expression and Improve Fruit Set in Trees
[16]	2019	Effects of Zinc Oxide Nanoparticles on In Vitro Growth of 'Manfalouty' and 'Wonderful' Pomegranate Cultivars.	Varied ZnO-NP Doses in Woody Plant Medium: A Study with Six Concentrations (0-10 mg/L)	Optimal Effects of 2.5 mg/L ZnO-NPs Concentration on Plant Growth and Physiology
[18]	2015	Evaluation of banana fruit ripeness using image processing methodology.	Mean color intensity algorithm and ANOVA.	85%.
[20]	2013	Evaluating the physico-chemical characteristics and mineral concentrations in pomegranate cv. 'Hicaznar' at three developmental stages.	Statistical analysis	Developmental Stage Effects on Physicochemical Traits and Mineral Concentrations in Fruits, Arils, and Soluble Solids
[21]	2013	Pomegranate Fruit Growth: Exploring Developmental Changes in Physical and Physiological Attributes and Texture Dynamics from Formation to Ripening.	Aril's textural dynamics.	Optimal Harvest Timing Identification and Readiness Assessment Tool for Fruits.

images. This paper discusses a plant disease detection system tailored for pomegranates, enhancing algorithm efficiency and accuracy by employing Grabcut segmentation for Region of Interest (ROI) extraction. Different segmentation techniques, including edge, threshold, and regions, were utilized. The algorithm was designed to identify three pomegranate diseases: bacterial blight, borer, and cercospora, with accompanying preventive measures suggested based on the identified disease. The overall accuracy of disease detection was determined to be 85%.

The study [15] examines how macronutrient availability affects the reproductive development of two varieties of pomegranates over a span of three years. The study involved cultivating the trees in containers and examining their responses to increased levels of nitrogen (N), phosphorus (P), and potassium (K) in the irrigation solution. The findings suggested that the andromonoecy rates were impacted by nutrient levels in the initial year, particularly with higher concentrations of nitrogen and phosphorus leading to a higher proportion of hermaphrodites. Elevated phosphorus levels were found to be positively correlated with the overall number of hermaphrodites per tree, while an increased nitrogen concentration in the irrigation solution had a positive influence on fruit set and aril number. However, the study had limitations, such as focusing solely on macronutrient effects and not considering other influencing factors. The examination was restricted to two specific cultivars in containers, potentially not fully representing field conditions. Future research should explore the impact of additional factors like temperature and light on pomegranate reproductive development and consider a broader range of cultivars and field experiments for a more comprehensive understanding of fertilization requirements.

The study [16] investigated the impact of zinc oxide nanoparticles (ZnO-NPs) on the growth of two valuers of pomegranate cultivars, 'Manfalouty' and 'Wonderful,' within an in vitro environment. Six different doses of ZnO-NPs, ranging from 0 to 10 mg/L, were introduced into a Woody Plant Medium (WPM). Morphophysiological analysis revealed that a concentration of 2.5 mg/L of ZnO-NPs produced the most favorable outcomes in terms of proliferation rate, shoot length, biomass, and total chlorophyll content compared to the control group. However, concentrations exceeding 2.5 mg/L exhibited adverse effects on plant growth and related physiological parameters. It is important to acknowledge the study's limitation, as the in vitro conditions may not entirely replicate the growth patterns of pomegranate plants in natural field conditions. Subsequent research is warranted to explore the impact of ZnO-NPs on pomegranate growth in field settings to validate these findings.

The research [20] focused on evaluating the physico-chemical characteristics and mineral concentrations in pomegranate cv. 'Hicaznar' at three developmental stages: immature, unripe, and fully ripe. The objective was to investigate how the developmental stage affects fruit properties and mineral concentrations. Additionally, the study aimed to assess the potential contributions of pomegranate consumption to recommended daily mineral intakes. The analysis included essential minerals such as P, K, Ca, Mg, Na, Fe, Mn, Zn, and Cu in pomegranates grown in Antalya, Turkey. SAS software was utilized for statistical analyses. Results showed that physico-chemical characteristics and mineral concentrations were significantly influenced by the developmental stage, with variations observed in fruit weight, aril weight, and soluble solid content. Notably, potassium (K), calcium (Ca), and manganese (Mn) made substantial contributions to mineral intake. However, the limitation of their study is that insufficient material prevented the determination of minerals in the immature stage. Future research could explore variations in nutrient composition among different pomegranate species and the impact of farming conditions on mineral concentrations.

The research [21] investigated the progression and characteristics of pomegranate fruit growth, examining changes in physiological and physical attributes, as well as texture dynamics during development and ripening. Two cultivars, 'Bhagwa' and 'Ruby', were observed across two distinct seasons. Differences in the development of fruits, respiration rates, and physico-textural characteristics were observed across five stages of maturity. Respiration rate decreased with maturity, peaking in immature fruits and reaching its lowest in fully ripe ones. Ethylene gas was not observed throughout the fruit development process. The enhancement of fruit pigmentation was evident with advancing maturity. The textural dynamics of the aril demonstrated an increasing trend in both bioyield force and elasticity as maturity advanced. The study identified the optimal harvesting time and provided a tool for assessing fruit readiness. Future research should consider incorporating fruit biochemical attributes when evaluating readiness for harvest.

The study introduced a real-time monitoring approach for assessing the growth state of strawberry fruits through an enhanced YOLOX model termed SDNet in [18]. This algorithm integrates a self-designed feature extraction module and a normalized attention module to improve spatial interaction and detection accuracy. To enhance prediction accuracy, the latest SIOU objective loss function was employed. SDNet successfully monitors strawberry fruits across five growth states, achieving an mAP of 94.26%, precision of 93.15%, and recall of 90.72%. Notably, the monitoring speed is 30.5 ms, surpassing the YOLOX model's speed with no substantial changes in the model size. Similarly, in a study [22], the SpectralGPT model was introduced for the image classification task.

In the realm of learning-based small object detection methods, there exists a notable reliance on the classification backbone network. However, this reliance often leads to challenges such as the loss of tiny objects and limitations in feature distinguishability as the network depth increases. Addressing this issue, the UIU-Net (U-Net in U-Net) approach emerges as a promising solution for detecting small objects within images. As the name suggests, UIU-Net incorporates a miniature U-Net architecture within a larger U-Net backbone. This innovative design facilitates multi-level and multi-scale representation learning of objects, thereby enhancing the model's ability to detect small objects accurately and efficiently. Wu et al. [23] have made significant strides in this domain by introducing the UIU-Net approach specifically tailored for the detection of small objects in Infrared images. Their work demonstrates the effectiveness of UIU-Net in addressing the challenges associated with small object detection, particularly in Infrared imagery. By embedding a miniature U-Net architecture within a larger U-Net backbone, UIU-Net enables enhanced feature representation and improved object detection capabilities, making it a valuable asset in various applications, including surveillance, medical imaging, and remote sensing.

The research aimed to create a novel image processing method for evaluating the maturity stage of fresh banana fruit based on color and size attributes derived from their images in [19]. A dataset of 120 images, encompassing 40 images from each maturity stage (under-mature, mature, and over-mature), was utilized for algorithm development and accuracy assessment. Image processing techniques were applied to extract various features, including mean color intensity, area, perimeter, major axis length, and minor axis length. Analysis of variance (ANOVA) was conducted to assess the significance of these features in predicting banana fruit maturity. Subsequently, two classifier algorithms, one based on mean color intensity and the other on area, were developed and evaluated for their accuracy in maturity detection. The mean color intensity algorithm demonstrated a high accuracy of 99.1% in classifying banana fruit maturity, while the area algorithm achieved 85% accuracy in detecting under-mature fruit.

III. PROPOSED METHODOLOGY

The research focused on predicting pomegranate growth stages through a comprehensive approach to materials and methods. To initiate this investigation, the primary materials encompassed a diverse set of pomegranate orchards representing various geographical regions and cultivation practices. Camera sensors-based imagery and remote sensing data are also incorporated to extract valuable information related to vegetation indices and canopy characteristics.

Our proposed methodology framework centers on predicting the five growth stages of pomegranates through a high-performance model, as depicted in Figure 1. We utilized a standard dataset of pomegranate growth stage images, employing both machine and deep learning approaches.

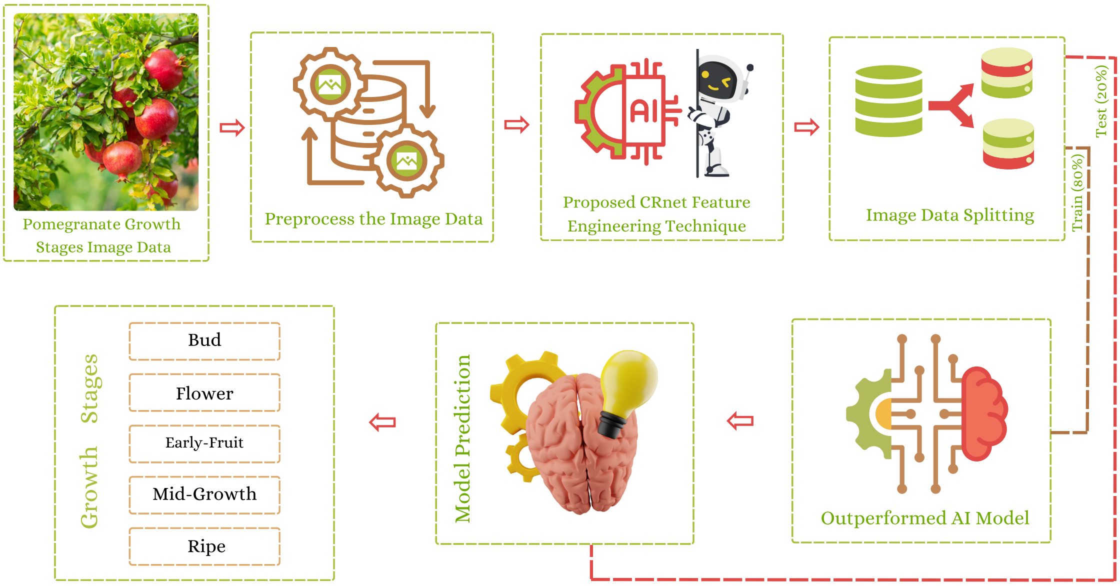

FIGURE 1. Examining the workflow architecture of the newly introduced method for detecting the growth stage of pomegranates.

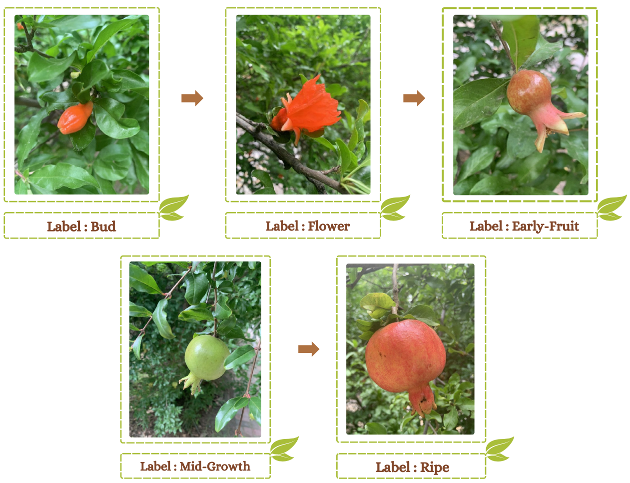

FIGURE 2. The pomegranates image data analysis with their target label.

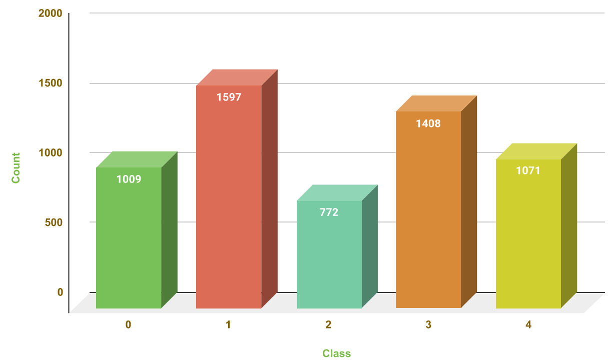

FIGURE 3. The pomegranates image data distribution analysis with their target label.

Subsequently, basic preprocessing techniques, including image data mapping and formatting, were applied. A novel transfer learning-based CRnet feature engineering is proposed, aiming to extract rich-level features from the image data and enhance the performance accuracy of growth stage predictions. The transfer features are then divided into two sets, with an 80:20 ratio for training and validation (80% for training and 20% for validation). The tuned, outperforming AI approach, demonstrating superior performance, is then employed to classify pomegranate growth stages accurately based on the provided images.

A. POMEGRANATE GROWTH STAGE IMAGES

Our proposed novel study utilizes the publicly accessible pomegranate growth stage images dataset from the Mendeley Data [24] repository for experimentation. This dataset comprises 5857 files classified into five classes: Bud, Flower, Mid-growth, Early-Fruit, and Ripe, as depicted in Figure 2. The analysis reveals that the Bud (0) class consists of 1009 image samples, Flower (1) has 1597 image samples, Early-Fruit (2) contains 772 image samples, Mid-growth (3) includes 1408 image samples, and Ripe (4) has 1071 image samples. A distribution analysis highlights the imbalanced nature of image labels. Additionally, Figure 3 illustrates the data analysis of pomegranate growth stages with their corresponding target labels.

B. IMAGE PREPROCESSING

In the initial phase of our study, we encountered an unformatted dataset consisting of five folders labeled as Bud, Flower, Mid-Growth, Early Fruit, and Ripe, as shown in the graphical representation above in Figure 5. The original dataset's main folder root contains several folders. We have

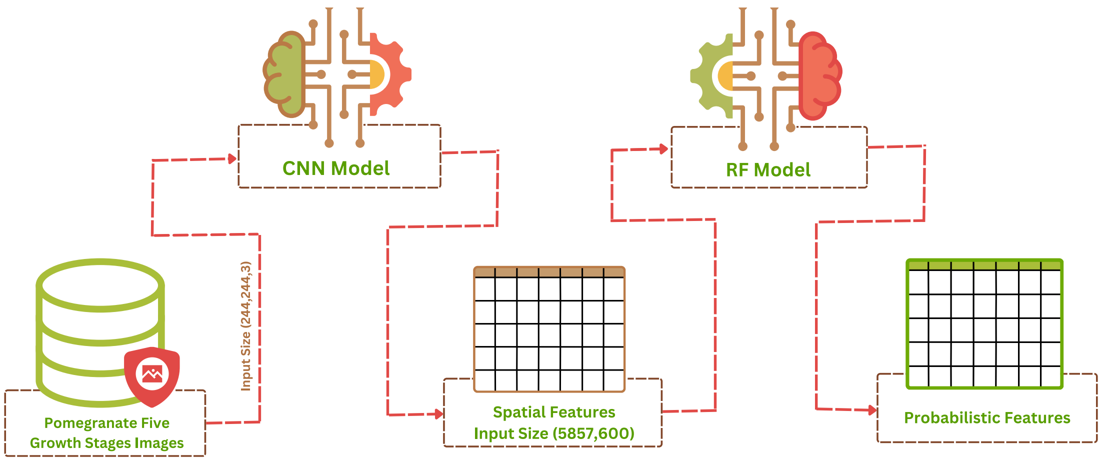

FIGURE 4. Conducting a comprehensive architectural analysis of the workflow for our innovative feature engineering method introduced for pomegranate images.

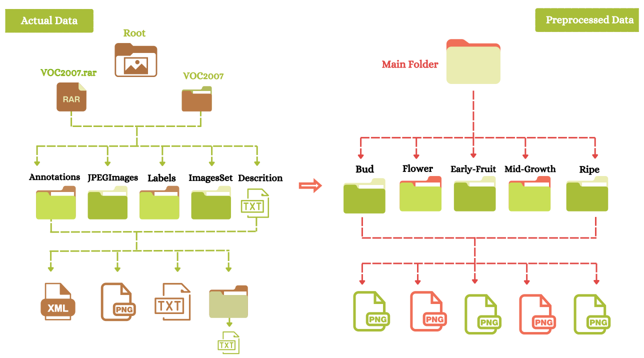

FIGURE 5. The examination involved an analysis of the preprocessing steps applied to image data.

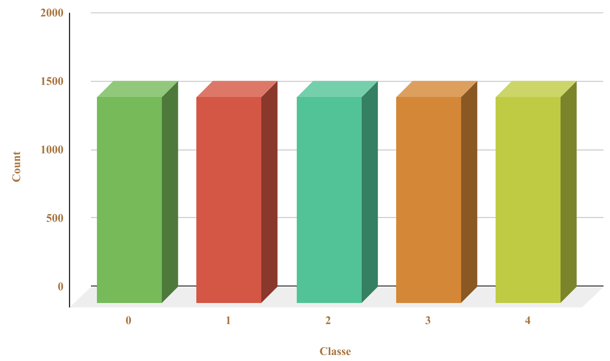

FIGURE 6. The target class images data distribution analysis after augmentations.

preprocessed and formatted the image dataset into label-wise folders, ensuring that each target class folder contains images belonging to it. Subsequently, we utilized the preprocessed image data to conduct our research experiments.

C. TRANSFER LEARNING BASED NOVEL FEATURE ENGINEERING

A novel CRnet approach is introduced for feature engineering from pomegranate fruit growth stage image data, as depicted in Figure 4. The CRnet technique, a novel method, amalgamates two transfer learning approaches to create a distinct feature set. Initially, spatial features are extracted using a Convolutional Neural Network (CNN) from a dataset of pomegranate growth stage images. Subsequently, these spatial features are fed into a Random Forest (RF). Then, a new probabilistic feature set is derived from the spatial feature data using a random forest model as transfer learning [25]. This probabilistic feature set is then employed in the development of advanced machine learning methods for effectively classifying pomegranate image data based on growth stages. The innovative transfer learning-based feature significantly advances the accuracy of predicting pomegranate growth stages, achieving high-performance scores.

1) CNN BASED SPATIAL FEATURES

In the realm of pomegranate growth stage classification, CNN plays a pivotal role in spatial feature extraction from images [26]. Leveraging their ability to automatically learn hierarchical representations, CNNs discern intricate patterns within pomegranate images, capturing nuances indicative of distinct growth stages. This research utilized the power of CNN-based spatial feature extraction to enhance the precision and efficiency of pomegranate growth stage classification, contributing to the optimization of agricultural monitoring and management practices. The CNN-based spatial feature extraction can be represented as follows:

$$\text{Input Image: } X \in \mathbb{R}^{H\times W\times C} \quad \text{(Height, Width, Channels)}$$

Convolutional Layer 1:

$$Z^{[1]} = \text{ReLU}\left(W^{[1]} * X + b^{[1]}\right)$$

Pooling Layer 1:

$$A^{[1]} = \text{MaxPooling}\left(Z^{[1]}\right)$$

Convolutional Layer 2:

$$Z^{[2]} = \text{ReLU}\left(W^{[2]} * A^{[1]} + b^{[2]}\right)$$

Pooling Layer 2:

$$A^{[2]} = \text{MaxPooling}\left(Z^{[2]}\right)$$

$$\vdots$$

Fully Connected Layer:

$$A^{[L-1]} = \text{Flatten}(A^{[L-1]})$$
$$Z^{[L]} = W^{[L]} \cdot A^{[L-1]} + b^{[L]}$$
$$\text{Output: } Y = \text{Softmax}(Z^{[L]}) \tag{1}$$

where:

- H and W are the width and height of the input image, respectively.
- C is the number of data channels in the input image.
- L is the number of layers in the network.
- $W^{[l]}$ and $b^{[l]}$ are the biases and weights of layer l.
- $*$ denotes the convolution operation.
- ReLU is the rectified linear unit activation function.
- MaxPooling is the max pooling operation.
- Softmax is the softmax activation function for classification spatial feature extraction.

2) RF BASED PROBABILISTIC FEATURES

Then the class probabilities feature [27] are extracted using the RF method from the CNN-based spatial features of pomegranate growth stage images. Let X be the input data representing CNN-based spatial features. The RF predicts class probabilities using the following equation:

$$P(y_i|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip})}}$$

where:

$P(y_i|X)$ is the probability values of class y_i given input X,

β_0 is the intercept value term,

$\beta_1, \beta_2, \ldots, \beta_p$ are coefficients values associated with features:

$X_{i1}, X_{i2}, \ldots, X_{ip}$.

The `predict_proba(X)` function of the RF calculates the class probabilities as follows:

$$\texttt{predict\_proba(X)} = [P(y_1|X), P(y_2|X), \ldots, P(y_k|X)]$$

where k is the number of classes.

Algorithm 1 contains the step-by-step workflow of our novel proposed transfer learning approach.

Algorithm 1 CRnet Algorithm

Input: Pomegranate growth stage images data.
Output: Transfer learning for novel features.
initiate;
1- $S_{cnn} \longleftarrow CNN_{prediction}(X)$ // $X \in pomegranateimageset$, here X is actual image data and S_{cnn} is extracted rich level spatial features set.
2- $S_{rf} \longleftarrow RF_{probabilities\,prediction}(S_{cnn})$ // here S_{rf} is the extracted novel probabilistic based features set.
3- $S_{prob} \longleftarrow S_{rf}$ // here S_{prob} is the final probabilistic-based rich features set used for pomegranate growth stage detection.
end;

D. SMOTE BASED OVERSAMPLING

After image preprocessing and data formatting, we identified that these folders contained images with uneven class distribution. Acknowledging the significance of addressing this imbalance to ensure robust model training and accurate predictions across all classes, we incorporated the Synthetic Minority Over-sampling Technique (SMOTE) during the preprocessing stage. SMOTE [28], a widely adopted technique, aims to alleviate class imbalances by generating synthetic samples of the minority class. This involves interpolating feature vectors of minority class instances, effectively augmenting the dataset and reducing the dominance of majority classes. By adopting this approach, we aimed to achieve a more balanced representation of each class (as shown in Figure 6), enhancing overall model performance and enabling the trained model to generalize effectively across all stages of pomegranate growth, from Bud to Ripe.

E. IMAGE DATA SPLITTING

Splitting a dataset is a crucial step in supervised machine learning, aiming to create distinct subsets for model training and performance evaluation. In this study, a splitting ratio of 80:20 is employed, allocating 80% of image data for model training and the remaining 20% for testing. The training set facilitates parameter fitting, while the test set validates the model's performance on unseen data. This strategy mitigates overfitting, a prevalent issue when models are trained on insufficient data.

F. APPLIED ARTIFICIAL INTELLIGENCE METHODS

The integration of artificial intelligence (AI) methods in agriculture has emerged as a promising avenue for advancing precision farming practices. One particularly intriguing application lies in the prediction of pomegranate growth stages, a critical aspect of orchard management. As the field continues to evolve [29], [30], the fusion of AI and agriculture holds considerable promise for sustainable and efficient cultivation practices, ensuring that farmers can harness cutting-edge technology to address the complexities of pomegranate cultivation and make well-informed decisions throughout the growth cycle.

1) CONVOLUTIONAL NEURAL NETWORK

The utilization of Convolutional Neural Networks (CNNs) [31] in agricultural applications, particularly for predicting pomegranate growth stages, has emerged as a promising and effective method. The CNN method involves the analysis of images capturing various growth stages of pomegranate trees. Through a hierarchical arrangement of convolutional layers, the network learns intricate features and patterns inherent in these images, enabling it to discern subtle differences between different growth stages. The convolutional filters effectively extract spatial hierarchies and relevant features, facilitating the network's ability to recognize the unique visual cues associated with distinct phases of pomegranate development. The layered data architecture of used CNN is illustrated in Table 2.

TABLE 2. The layered stack analysis of applied convolutional neural network.

Layer (Type)	Output Shape	Parameters
Conv2D Layer	(None, 222, 222, 32)	896
MaxPooling2D Layer	(None, 111, 111, 32)	0
Dropout Layer	(None, 111, 111, 32)	0
Flatten Layer	(None, 394272)	0
Dense Layer	(None, 16)	6308368
Dense Layer	(None, 600)	10200
Total Parameters	6319464	

2) RANDOM FOREST

The Random Forest (RF) [32] method employs an ensemble of decision trees to predict pomegranate growth stages with notable accuracy. By combining the predictions of multiple trees, RF mitigates overfitting and enhances generalization. The method leverages the diverse perspectives of individual trees, enabling robust predictions based on features relevant to pomegranate growth. RF's ability to handle complex relationships within the data makes it a powerful tool for accurate and reliable prediction of pomegranate development stages. The overall prediction can be expressed as:

$$\hat{Y}(x) = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \tag{2}$$

where:

- $\hat{Y}(x)$ is the predicted pomegranate growth stage for input data x.
- N is the number of used decision trees in the forest.
- $f_i(x)$ is the prediction values of the i-th decision tree.

3) LOGISTIC REGRESSION

Logistic Regression (LR) [33], [34] is a statistical method commonly utilized for pomegranate growth stage prediction. By analyzing relevant features such as soil quality, temperature, and humidity, LR assigns probabilities to each growth stage. The model uses a logistic function to transform these probabilities into discrete classifications, aiding in accurate stage identification. Its simplicity, interpretability, and efficiency make Logistic Regression a valuable tool in predicting and understanding the progression of pomegranate growth. The LR equation is given by:

$$P(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}} \tag{3}$$

where:

$P(Y=1)$ is the probability values of the event Y happening,

e is the base values of the natural logarithm,

β_0 is the intercept term,

$\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients values of the features: $X_1, X_2, \ldots, X_n$.

4) K-NEIGHBORS CLASSIFIER

The K-Neighbors Classifier (KNC) [35] method operates by utilizing the k-nearest neighbors algorithm to predict pomegranate growth stages. It assesses the similarity of a given pomegranate sample to its k-nearest neighbors in a training dataset, classifying the growth stage based on the most prevalent stages within that neighborhood. The KNC's effectiveness lies in its ability to capture local patterns and make predictions based on the characteristics of neighboring samples. The basic mathematical equation for the KNC is given by:

$$\hat{y}(x) = \arg\max_j \left(\sum_{i \in \mathcal{N}(x)} I(y_i = j) \right) \tag{4}$$

where:

$$\hat{y}(x): \text{Predicted class for the input } x$$
$$\mathcal{N}(x): \text{Set of K-nearest neighbors of } x$$
$$I(y_i = j): \text{equal to 1 if } y_i = j, \text{ and 0 otherwise}$$

5) GAUSSIAN NAIVE BAYES

The Gaussian Naive Bayes (GNB) [36] method for predicting pomegranate growth stages relies on probability theory and statistical techniques. GNB assumes that features are conditionally independent given the class labels, making it particularly suitable for applications with continuous data, such as growth stage prediction. By modeling the distribution of feature values using Gaussian distributions, GNB calculates the likelihood of a particular growth stage given observed feature values. This method proves effective in capturing patterns in the data and providing accurate predictions for different stages of pomegranate growth. The GNB formula for predicting pomegranate growth stages can be represented as follows:

$$P(y|x_1, x_2, \ldots, x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1, x_2, \ldots, x_n)} \tag{5}$$

Here,

- $P(y)$ is the prior probability of the class y (pomegranate growth stage).

- $P(x_i|y)$ is the conditional data probability of feature x_i given the class y.
- $P(x_1, x_2, \ldots, x_n)$ is the evidence, which is a normalization term to make the probabilities sum to 1.

G. HYPER-PARAMETER TUNING

The optimization of hyperparameters has emerged as a pivotal phase in machine learning for pomegranate growth stage prediction. The procedure involves experimenting with diverse hyperparameter combinations and assessing the model's efficacy on a test set. The primary objective of hyperparameter tuning is to identify the hyperparameter set that yields optimal performance on the test set. A detailed analysis of hyperparameter optimization for our applied techniques is presented in Table 3. We utilized k-fold cross-validations and a recursive process of training and testing for the identification of hyperparameters for applied approaches.

TABLE 3. Analyzing the hyperparameter tuning of implemented artificial intelligence methodologies.

Technique	Hyperparameter Values
RF	random_state=0, max_depth=300, n_estimators=300, min_samples_leaf=1
KNC	n_neighbors=5, algorithm='auto', weights='uniform', leaf_size=30,p=2
LR	random_state=0,penalty='l2', dual=False, tol=0.0001, C=1.0,verbose=0
GNB	priors=None, var_smoothing=1e-09
CNN	optimizer='adam', metrics=['accuracy'], loss='categorical_crossentropy'

IV. RESULTS AND DISCUSSIONS

In this section, we delve into the assessment and analysis of the outcomes obtained from the results of artificial intelligence techniques. We provide a comparative depiction of the experimental setup and performance results concerning pomegranate image data related to pomegranate growth stages. Key performance metrics are employed to gauge the efficacy of the model.

A. EXPERIMENTAL SETUP

During the experimental setup, the machine learning models were constructed using widely used Python programming libraries, including scikit-learn, Keras, and TensorFlow. The research is conducted in an online Google Colab [37] setting, making use of a high-performance GPU backend equipped with 13 GB of RAM and 90 GB of disk space. The experiments utilized a computational framework with an Intel(R) Xeon(R) processor. The training and evaluation of model performance were carried out using the Python 3 programming language. The evaluation criteria encompassed recall, accuracy, precision, F1, and time complexity, serving as benchmarks for gauging the effectiveness of the machine learning models for predicting pomegranate growth stages.

B. CONVOLUTIONAL NEURAL NETWORK RESULTS

The pomegranate growth stage images undergo analysis using a classical CNN approach, and an assessment is examined during the training. Employing a time series-based approach, a CNN is trained over 20 epochs, as depicted in Figure 7. The results of this analysis indicate a reduction in validation loss scores as the epochs progress. This investigation illustrates the classical CNN neural network's capacity to grasp intricate patterns from the pomegranate growth stage images over successive epochs, refining the network weights for optimal performance. At epoch 20, the highest validation accuracy attained is above 56%, while at epoch four, validation accuracy surpasses 65%. This analysis concludes that the classical CNN achieves moderate performance scores during training but falls short of achieving the highest possible performance.

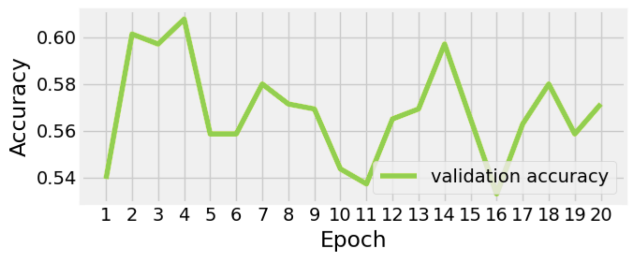

FIGURE 7. The performance evaluations analysis of the CNN approach using time series.

TABLE 4. The outcomes of employing a classical convolutional neural network for forecasting the growth stages of pomegranates.

Accuracy	Target	Precision	Recall	F1-score	Support
0.54	Bud	0.32	0.32	0.30	199
	Flower	0.26	0.26	0.28	144
	Early-Fruit	0.72	0.72	0.56	333
	Mid-growth	0.62	0.62	0.66	288
	Ripe	0.61	0.61	0.77	208
	Average	0.55	0.54	0.54	1172

Table 4 illustrates a performance comparison of the classical CNN when applied to unseen data in deep learning. The examination indicates that, in the testing phase, the CNN attained the maximum recall score of 54%. The associated performance measures for accuracy, precision, and F1 are 55%, 54%, and 54%, respectively. This assessment leads to the conclusion that the CNN exhibited suboptimal performance in classifying pomegranate growth stages based on growth stage images. This analysis provides a thorough examination of the performance metric scores for the applied classical CNN. We also compared the performance scores of CNN through histogram-based analysis as shown in Figure 8. However, there is still room for improvement in performance scores, suggesting the need for an advanced approach.

The confusion matrix-based validation analysis for the applied classical CNN technique is illustrated in Figure 9. This matrix serves as a tabular representation summarizing the model's predictions in comparison to the actual labels

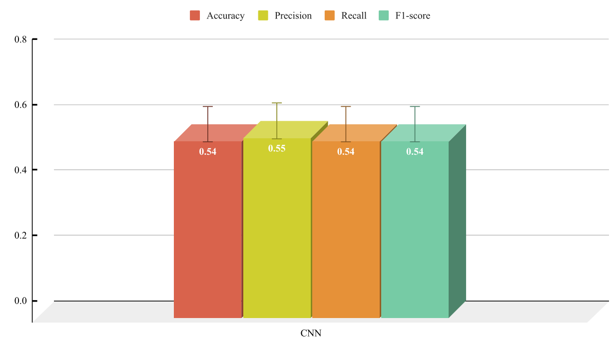

FIGURE 8. Histogram-based comparisons of CNN based image classification approach.

in the dataset. Examining the metrics within the confusion matrix allows us to discern the model's strengths and weaknesses, pinpointing areas that may require enhancement. The analysis indicates that the applied CNN exhibited suboptimal performance scores when dealing with pomegranate growth stage prediction image data. The applied CNN method resulted in a high error rate, particularly in the classification of pomegranate growth stage images. This analysis sum up that the CNN achieved a high error rate for stages 0 and 1 during unseen data prediction.

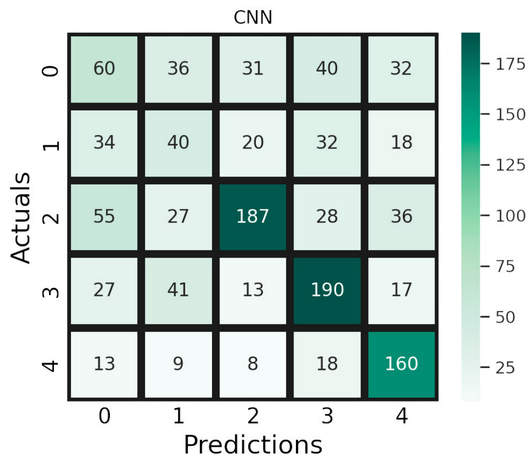

FIGURE 9. The confusion matrix validation analysis of applied classical CNN approach.

C. RESULTS WITH NOVEL PROPOSED METHOD

This section examines the performance results comparisons utilizing our novel proposed transfer learning-based feature engineering. Table 5 displays an assessment of the performance contrast among different machine learning techniques applied alongside recently derived features. The results indicate that each machine learning technique, namely KNC, LR, and GNB, achieved good performance scores of 0.97, showcasing comparable accuracy. Additionally, the performance results for each class demonstrated optimal scores. The RF technique stood out with the highest accuracy performance score of 0.98. In summary, the utilization of novel extracted spatial and probabilistic features proves to be the most effective approach for classifying growth stages in pomegranate images.

TABLE 5. The performance analysis is conducted on applied machine learning methods utilizing a newly proposed feature engineering approach.

Approach	Accuracy	Target	Precision	Recall	F1
RF	**0.98**	Bud	0.97	0.98	0.97
		Flower	0.95	0.98	0.97
		Early-Fruit	0.99	0.97	0.98
		Mid-growth	0.99	0.97	0.98
		Ripe	0.98	0.98	0.98
		Average	**0.98**	**0.98**	**0.98**
KNC	0.97	Bud	0.96	0.97	0.96
		Flower	0.95	0.97	0.96
		Early-Fruit	0.99	0.98	0.98
		Mid-growth	0.98	0.96	0.97
		Ripe	0.99	0.99	0.99
		Average	0.97	0.97	0.97
LR	0.97	Bud	0.96	0.98	0.97
		Flower	0.95	0.98	0.96
		Early-Fruit	0.99	0.96	0.97
		Mid-growth	0.99	0.96	0.98
		Ripe	0.98	0.98	0.98
		Average	0.97	0.97	0.97
GNB	0.97	Bud	0.94	0.98	0.96
		Flower	0.95	0.97	0.96
		Early-Fruit	0.99	0.96	0.97
		Mid-growth	0.99	0.96	0.97
		Ripe	0.98	0.98	0.98
		Average	0.97	0.97	0.97

The results validation analysis, based on confusion matrices, for all applied machine learning approaches incorporating newly created image features, is illustrated in Figure 10. The utilization of the newly proposed features resulted in high-performance scores, as evidenced by the analysis of the confusion matrix. The analysis indicates that the proposed RF approach only predicts incorrectly for 39 pomegranate images. This examination suggests that the implementation of probabilistic features in machine learning methods led to a reduced error rate in the classification of pomegranate growth stage images.

Figure 12 depicts a comparative performance analysis using histogram-based bar charts for applied machine learning methods incorporating newly proposed features. The analysis reveals a notable surge in accuracy scores, particularly when employing proposed features derived from the spatial characteristics of pomegranate images. The RF technique proposed in this research attains the highest accuracy score, reaching 98%. The findings suggest that all employed machine learning methods excel in accurately classifying the growth stages of pomegranate images.

The CRnet layer's spatial feature extraction from pomegranate images is illustrated in Figure 11. The layers in CRnet are responsible for detecting local patterns such as edges, textures, and simple shapes, gradually combining them to form higher-level representations in deeper layers. Visualizing these spatial features can provide valuable insights into the network's learning process and highlight the regions of an image that contribute significantly to the

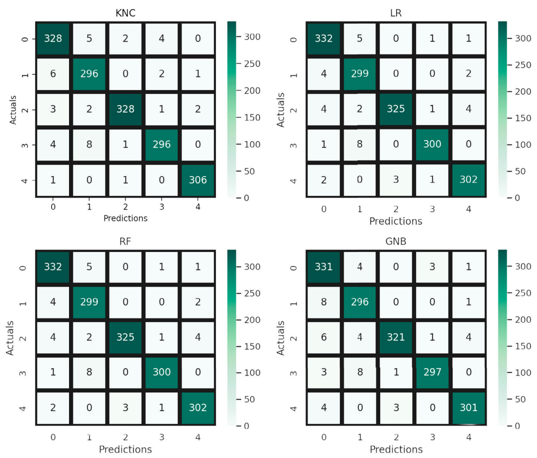

FIGURE 10. The confusion matrix validation analysis of applied machine learning methods using proposed features.

TABLE 6. The evaluation of performance validations for employed machine learning techniques through the proposed feature engineering.

Technique	K-fold Accuracy(%)	Standard deviation(+/-)
RF	0.9803	0.0043
KNC	0.9763	0.0036
LR	0.9796	0.0049
GNB	0.9770	0.0063

TABLE 7. The examination of Run-time Computational Complexity of employed machine learning algorithms.

Technique	Runtime Computational Cost (Seconds)
RF	3.741
KNC	0.039
LR	0.202
GNB	0.005
CNN	2.015

network's decision-making. This analysis concludes that the transfer learning-based proposed feature engineering extracts rich-level features for predicting the pomegranate's growth stages.

D. CROSS-VALIDATION-BASED K-FOLD ANALYSIS

The results of k-fold cross-validation for applied machine learning approaches are presented in Table 6. This cross-validation analysis evaluates the generalization performance of each employed model. The newly created set of feature data undergoes validation across ten folds for each technique applied in this section. The findings reveal that the LR technique achieves a commendable k-fold accuracy score of 0.97, followed by KNC and GNB. Notably, our proposed RF approach, which utilizes probability features, attains the highest accuracy of 0.98. Overall, the analysis affirms the robust validation and generalization capabilities of all applied techniques in classifying pomegranate growth stages based on image data.

E. ANALYSIS OF RUNTIME COMPUTATIONAL COMPLEXITY

The research involves a comparative performance analysis of runtime computations for applied machine learning approaches, with a focus on the newly created feature set, as depicted in Table 7. The novel features facilitate a faster construction of machine learning models. The GNB model demonstrates the shortest training time. Despite its swift training, GNB exhibits a slightly lower accuracy of 97% when utilizing the proposed features. In contrast, the proposed RF apporach requires a bit longer training time compared to other techniques but attains the highest accuracy in predicting pomegranate growth stages.

F. ABLATION STUDY

In this subsection, we present the results of the ablation study conducted to assess the performance and functionality of our ML-based system by systematically removing specific components. The primary objective of the ablation study was to understand the contribution and significance of each component to the overall performance and behaviour of the system.

Specifically, we focused on evaluating the impact of our novel approach, CRnet, and Random Forest (RF) in comparison to traditional ML models, including Convolutional Neural Network (CNN), k-Nearest Neighbors Classifier (KNC), Gaussian Naive Bayes (GNB), and Logistic Regression (LR).

Upon removal of CRnet and RF, we observed noteworthy results. Our introduced model consistently outperformed state-of-the-art methods with a remarkable accuracy of 98% in predicting pomegranate growth stages. This demonstrates the effectiveness and superiority of our approach over traditional ML models in this domain.

The findings from the ablation study underscore the importance of our novel approach and its significant contribution to enhancing the performance of the ML-based system for predicting pomegranate growth stages.

Overall, the results of the ablation study reinforce the robustness.

G. STATE-OF-THE-ART STUDIES COMPARISONS

Table 8 presents a comprehensive comparison of the performance of our new proposed study's method with state-of-the-art studies. To ensure fairness, we considered studies published between 2020 and 2023. Earlier research predominantly employed deep learning techniques, achieving a maximum performance score of 96%, which is relatively modest. In our novel research approach, we utilized a transfer learning-based novel feature engineering apporach to enhance performance. The findings indicate that our proposed model, employing CNN and RF with new transfer features, achieved the highest performance scores, reaching 98% accuracy in classifying images of pomegranate's five growth stages. This research outperformed state-of-the-art approaches during comparison.

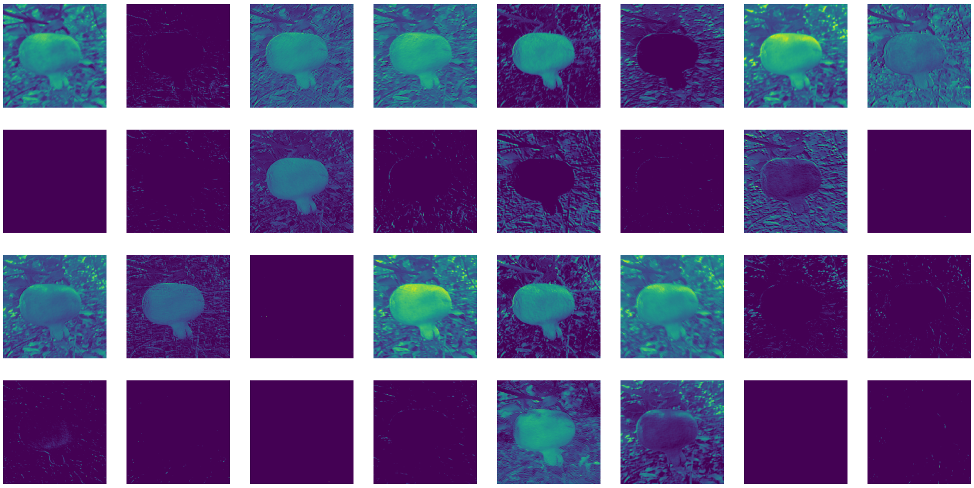

FIGURE 11. The outcomes present sample layer representations of the proposed approach for the extraction of rich features from images captured during the pomegranate growth stage.

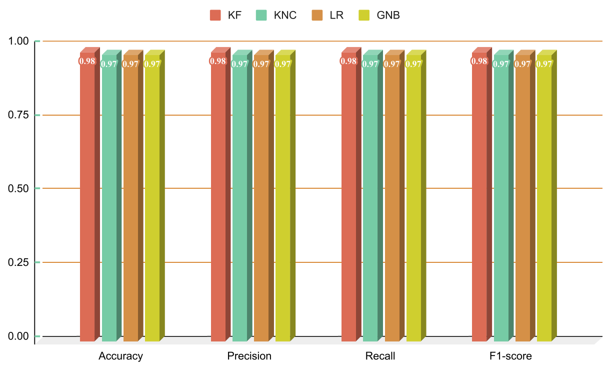

FIGURE 12. The performance evaluations of all applied machine learning methods using histogram-based comparisons.

TABLE 8. The performance comparison of the proposed approach with state-of-the-art studies.

Ref.	Year	Learning Type	Technique	Performance Accuracy (%)
[14]	2020	Machine Learning	GMM+ROI	85
[38]	2022	Machine Learning	LDA+NB	96
[39]	2022	Machine Learning	SVM	96
[40]	2023	Machine Learning	GLCM+SVM	83
[41]	2023	Deep Learning	ECAM-YOLOv5-BiFPN	91
Our	**2024**	**Transfer Learning**	**Novel CRnet**	**98**

V. CONCLUSION AND FUTURE DIRECTION

This study introduces an innovative approach for classifying pomegranate growth stages through advanced transfer learning and machine learning approaches. The proposed CRnet, a transfer learning-based novel feature engineering method, demonstrates high-performance classification of growth stages. CRnet employs a 2D-CNN to extract spatial features from pomegranate growth stage images, forming a probabilistic feature set with the random forest technique. This set is utilized in constructing machine learning-based models. We employed advanced classification methods, such as the CNN, RF, LR, GNB, and KNC. The proposed approach exhibited exceptional performance scores in comparison to existing state-of-the-art studies. The RF model presented in this study demonstrates exceptional performance, achieving a 98% accuracy across key metrics such as recall, f1, and precision. To enhance the reliability of machine learning and deep learning techniques, our approach includes the utilization of hyperparameter optimization and a cross-validation technique based on k-fold validation. Additionally, the computational complexity is determined.

A. FUTURE WORK

In future work, we plan to enhance our proposed model by reducing its computational runtime complexity. We aim to streamline the architecture of the proposed model layers. Additionally, we will design a mobile application that will implement our novel proposed model in the backend. This application will be capable of detecting pomegranate growth stages and providing timely solutions to farmers.

ACKNOWLEDGMENT

The authors would like to express their grateful to Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R330), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

REFERENCES

[1] A. S. Hussein, A. H. A. Abeed, A. R. A. Usman, and E. A. A. Abou-Zaid, "Conventional vs. nano-micronutrients as foliar fertilization for enhancing the quality and nutritional status of pomegranate fruits," *J. Saudi Soc. Agricult. Sci.*, vol. 47, p. 10, Sep. 2023.

[2] D. G. Maksudan and V. Minz, "Effect of organic and inorganic fertilizers on growth and economics of treatments of pomegranate *(Punica granatum L.)* under precision farming," *Pharma Innov. J.*, vol. 12, no. 7, pp. 2769–2772, 2023.

[3] G. Benedetti, F. Zabini, L. Tagliavento, F. Meneguzzo, V. Calderone, and L. Testai, "An overview of the health benefits, extraction methods and improving the properties of pomegranate," *Antioxidants*, vol. 12, no. 7, p. 1351, Jun. 2023.

[4] P. S. Mitkal and A. Jagadale, "Grading of pomegranate fruit using CNN," *Int. J. Adv. Res. Sci., Commun. Technol.*, vol. 3, no. 2, pp. 257–266, 2023.

[5] F. Moradinezhad and A. Ranjbar, "Foliar application of fertilizers and plant growth regulators on pomegranate fruit yield and quality: A review," *J. Plant Nutrition*, vol. 5, pp. 1–25, Nov. 2023.

[6] V. D. Vidanapathirana, A. H. L. D. K. Gimhan, S. R. L. Jayarathne, S. M. D. C. Navodya, D. Pandithage, and S. Rupasinghe, "Pomegranate farming monitoring system," *Int. J. Res. Eng., Sci. Manage.*, vol. 6, no. 10, pp. 83–88, 2023.

[7] P. Wakhare and S. Nedunchelíyan, "Study of effective pest management strategies for pomegranate orchards," *J. Surv. Fisheries Sci.*, vol. 10, no. 4, pp. 1772–1782, Apr. 2023.
[8] R. A. Jamadar, A. Sharma, and K. Wagh, "Combining generative adversarial networks with transfer learning for deep learning-based pomegranate plant leaf disease detection," in *Proc. Int. Conf. Smart Comput. Commun.* Cham, Switzerland: Springer, 2023, pp. 487–496.
[9] M. A. Khan, T. Akram, M. Sharif, K. Javed, M. Raza, and T. Saba, "An automated system for cucumber leaf diseased spot detection and classification using improved saliency method and deep features selection," *Multimedia Tools Appl.*, vol. 79, nos. 25–26, pp. 18627–18656, Jul. 2020.
[10] S. Aziz, K. Munir, A. Raza, M. S. Almutairi, and S. Nawaz, "IVNet: Transfer learning based diagnosis of breast cancer grading using histopathological images of infected cells," *IEEE Access*, vol. 11, pp. 127880–127894, 2023.
[11] V. Chouhan, S. K. Singh, A. Khamparia, D. Gupta, P. Tiwari, C. Moreira, R. Damasevicius, and V. H. C. De Albuquerque, "A novel transfer learning based approach for pneumonia detection in chest X-ray images," *Appl. Sci.*, vol. 10, no. 2, p. 559, Jan. 2020.
[12] V. G. Pokharkar, C. M. Gulave, and D. B. Yadav, "Economic impact of pomegranate research and extension on farm economy," *Ann. Horticulture*, vol. 11, no. 1, pp. 23–32, 2018.
[13] R. Tarai, U. Nayak, A. Panda, V. Sharma, V. Supe, M. Shete, and C. Dhumal, "Plant growth regulators in pomegranate," in *Proc. Plant Growth Regulators in Tropical and Sub-tropical Fruit Crops*. Boca Raton, FL, USA: CRC Press, 2022, pp. 535–563.
[14] D. M. Sharath, Akhilesh, M. G. Rohan, S. A. Kumar, and C. Prathap, "Disease detection in pomegranate using image processing," in *Proc. 4th Int. Conf. Trends Electron. Informat.*, Jun. 2020, pp. 994–999.
[15] S. Lazare, Y. Lyu, U. Yermiyahu, Y. Heler, G. Kalyan, and A. Dag, "The effect of macronutrient availability on pomegranate reproductive development," *Plants*, vol. 9, no. 8, p. 963, Jul. 2020.
[16] M. T. El-Mahdy and D. S. Elazab, "Impact of zinc oxide nanoparticles on pomegranate growth under in vitro conditions," *Russian J. Plant Physiol.*, vol. 67, no. 1, pp. 162–167, Jan. 2020.
[17] M. Nergiz, "YOLO-V7 based detection and classification of pomegranate fruits in different growing stages," ResearchGate, Tech. Rep. 3, 2023.
[18] Q. An, K. Wang, Z. Li, C. Song, X. Tang, and J. Song, "Real-time monitoring method of strawberry fruit growth state based on YOLO improved model," *IEEE Access*, vol. 10, pp. 124363–124372, 2022.
[19] D. S. Prabha and J. S. Kumar, "Assessment of banana fruit maturity by image processing technique," *J. Food Sci. Technol.*, vol. 52, no. 3, pp. 1316–1327, Mar. 2015.
[20] S. G. Ozlekci, S. Ercisli, F. Okturen, and S. Sonmez, "Physico-chemical characteristics at three development stages in pomegranate cv. 'Hicaznar,'" *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, vol. 39, no. 1, p. 241, Jan. 2013.
[21] O. A. Fawole and U. L. Opara, "Fruit growth dynamics, respiration rate and physico-textural properties during pomegranate development and ripening," *Scientia Horticulturae*, vol. 157, pp. 90–98, Jun. 2013.
[22] D. Hong, B. Zhang, X. Li, Y. Li, C. Li, J. Yao, N. Yokoya, H. Li, P. Ghamisi, X. Jia, A. Plaza, G. Paolo, J. A. Benediktsson, and J. Chanussot, "SpectralGPT: Spectral foundation model," 2023, *arXiv:2311.07113*.
[23] X. Wu, D. Hong, and J. Chanussot, "UIU-Net: U-Net in U-Net for infrared small object detection," *IEEE Trans. Image Process.*, vol. 32, pp. 364–376, 2023.
[24] R. A. J. Zhao. (Jul. 2023). *Pomegranate Images Dataset—mendeley Data*. Accessed: Dec. 30, 2023. [Online]. Available: https://data.mendeley.com/datasets/kgwsthf2w6/5
[25] A. Raza, K. Munir, M. S. Almutairi, and R. Sehar, "Novel class probability features for optimizing network attack detection with machine learning," *IEEE Access*, vol. 11, pp. 98685–98694, 2023.
[26] T. Guo, R. Wang, F. Luo, X. Gong, L. Zhang, and X. Gao, "Dual-view spectral and global spatial feature fusion network for hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 5512913.
[27] A. Raza, H. U. R. Siddiqui, K. Munir, M. Almutairi, F. Rustam, and I. Ashraf, "Ensemble learning-based feature engineering to analyze maternal health during pregnancy and health risk prediction," *PLoS One*, vol. 17, no. 11, Nov. 2022, Art. no. e0276525.
[28] A. Özdemir, K. Polat, and A. Alhudhaif, "Classification of imbalanced hyperspectral images using SMOTE-based deep learning methods," *Expert Syst. Appl.*, vol. 178, Sep. 2021, Art. no. 114986.
[29] A. Raza, I. Akhtar, L. Abualigah, R. A. Zitar, M. Sharaf, M. S. Daoud, and H. Jia, "Preventing road accidents through early detection of driver behavior using smartphone motion sensor data: An ensemble feature engineering approach," *IEEE Access*, vol. 11, pp. 138457–138471, 2023.
[30] A. M. Qadri, A. Raza, F. Eid, and L. Abualigah, "A novel transfer learning-based model for diagnosing malaria from parasitized and uninfected red blood cell images," *Decis. Anal. J.*, vol. 9, Dec. 2023, Art. no. 100352.
[31] S. Mei, R. Jiang, M. Ma, and C. Song, "Rotation-invariant feature learning via convolutional neural network with cyclic polar coordinates convolutional layer," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, 2023, Art. no. 5600713.
[32] D. A. Devyatkin, "Estimation of vegetation indices with random kernel forests," *IEEE Access*, vol. 11, pp. 29500–29509, 2023.
[33] A. Raza, A. M. Qadri, I. Akhtar, N. A. Samee, and M. Alabdulhafith, "LogRF: An approach to human pose estimation using skeleton landmarks for physiotherapy fitness exercise correction," *IEEE Access*, vol. 11, pp. 107930–107939, 2023.
[34] A. Raza, F. Rustam, B. Mallampati, P. Gali, and I. Ashraf, "Preventing crimes through gunshots recognition using novel feature engineering and meta-learning approach," *IEEE Access*, vol. 11, pp. 103115–103131, 2023.
[35] C. Gong, J. Demmel, and Y. You, "Scalable evidential K-nearest neighbor classification on big data," *IEEE Trans. Big Data*, early access, p. 12, Oct. 2023.
[36] M. S. Haque, M. S. Amin, S. Ahmad, M. A. Sayed, A. Raihan, and M. A. Hossain, "Predicting kidney failure using an ensemble machine learning model: A comparative study," in *Proc. 10th Int. Conf. Electr. Eng., Comput. Sci. Informat. (EECSI)*, Sep. 2023, pp. 31–37.
[37] A. Raza, K. Munir, M. S. Almutairi, and R. Sehar, "Novel transfer learning based deep features for diagnosis of down syndrome in children using facial images," *IEEE Access*, vol. 12, pp. 16386–16396, 2024.
[38] M. D. Nirmal, P. Jadhav, and S. Pawar, "Classification of pomegranate leaves diseases by image processing and machine learning techniques," *Cybern. Syst.*, vol. 10, pp. 1–15, Nov. 2022.
[39] M. D. Nirmal, P. Jadhav, and S. Pawar, "Pomegranate leaf disease classification using feature extraction and machine learning," in *Proc. 3rd Int. Conf. Smart Electron. Commun. (ICOSEC)*, Oct. 2022, pp. 619–626.
[40] S. Khatawkar, S. Jadhav, S. Sapate, P. Patil, and A. Shinde, "Disease detection on pomegranate fruits using machine learning approach," in *Proc. AIP Conf.*, vol. 2717, 2023, p. 15.
[41] L. He, H. Wei, and Q. Wang, "A new target detection method of ferrography wear particle images based on ECAM-YOLOv5-BiFPN network," *Sensors*, vol. 23, no. 14, p. 6477, Jul. 2023.

AISHA NASEER received the Bachelor of Science degree in software engineering from the Department of Computer Engineering, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan, Pakistan, in 2022, where she is currently pursuing the Master of Science degree with the Information Technology Program, actively pursuing academic interests that encompass data science, artificial intelligence, data mining, machine learning, deep learning, and image processing.

MADIHA AMJAD received the M.Sc. degree in electronics from Quaid-i-Azam University, Pakistan, in 2008, the M.S. degree in computer engineering from the University of Engineering and Technology, Pakistan, in 2011, and the Ph.D. degree from the National University of Sciences and Technology (NUST), Pakistan, in 2020. She is currently an Assistant Professor with the Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan. Her research interests include the design and optimization MAC layer schemes for hybrid VLC/RF networks, WSNs and molecular nanonetworks, resource optimization, clustering in unmanned vehicular area networks (UAV), and design of IoT-based solutions to solve indigenous problems.

ALI RAZA received the Bachelor of Science and M.S. degrees in computer science from the Department of Computer Science, Khwaja Fareed University of Engineering and Information Technology (KFUEIT), Rahim Yar Khan, Pakistan, in 2021 and 2023, respectively. He has published several articles in reputed journals. His current research interests include data science, artificial intelligence, data mining, natural language processing, machine learning, deep learning, and image processing.

KASHIF MUNIR received the B.Sc. degree in mathematics and physics from The Islamia University of Bahawalpur, Pakistan, in 1999, the M.Sc. degree in information technology from Universiti Sains Malaysia, in 2001, the M.S. degree in software engineering from the University of Malaya, Malaysia, in 2005, and the Ph.D. degree in informatics from the Malaysia University of Science and Technology, Malaysia, in 2015. He has been in the field of higher education, since 2002. After an initial teaching experience with courses in Binary College, Malaysia, for one semester, and Stamford College, Malaysia, for around four years. Later, he relocated to Saudi Arabia. He was with the King Fahd University of Petroleum and Minerals, Saudi Arabia, from September 2006 to December 2014. He moved to the University of Hafr Al Batin, Saudi Arabia, in January 2015. In July 2021, he joined the Khwaja Fareed University of Engineering and IT, Rahim Yar Khan, as an Assistant Professor with the IT Department. He has published journal articles, conference papers, book, and book chapters. His research interests are in the areas of cloud computing security, software engineering, and project management. He has been in the technical program committee of many peer-reviewed conferences and journals, where he has reviewed many research articles.

NAGWAN ABDEL SAMEE received the B.S. degree in computer engineering from Ein Shams University, Egypt, in 2000, and the M.S. degree in computer engineering and the Ph.D. degree in systems and biomedical engineering from Cairo University, Egypt, in 2008 and 2012, respectively. Since 2013, she has been an Assistant Professor with the Information Technology Department, CCIS, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. Her research interests include data science, machine learning, bioinformatics, and parallel computing. Her awards and honors include the Takafull Prize (Innovation Project Track), the Princess Nourah Award in Innovation, the Mastery Award in Predictive Analytics (IBM), the Mastery Award in Big Data (IBM), and the Mastery Award in Cloud Computing (IBM).

MANAL ABDULLAH ALOHALI received the Ph.D. degree in computer science from the University of Plymouth, U.K. She is an Assistant Professor with the Information Systems Department, CCIS, Princess Nourah bint Abdulrahman University (PNU), Saudi Arabia, where she is the Dean of CCIS. Her research interests reside in the areas of information systems, machine learning, and cyber security. She received the PNU's Research Excellence Award.