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# Image analysis and machine learning techniques for accurate detection of common mango diseases in warm climates

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**ABSTRACT**

Mangoes are valuable crops grown in warm climates, but they often suffer from diseases that harm both the trees and the fruits. This paper proposes a new way to use machine learning to detect these diseases early in mango plants. We focused on common issues like mango fruit diseases, leaf diseases, powdery mildew, anthracnose/blossom blight, and dieback, which are particularly problematic in places like Bangladesh. Our method starts by improving the quality of images of mango plants and then extracting important features from these images. We use a technique called k-means clustering to divide the images into meaningful parts for analysis. After extracting ten key features, we tested various ways to classify the diseases. The random forest algorithm stood out, accurately identifying diseases with a 97.44% success rate. This research is crucial for Bangladesh, where mango farming is essential for the economy. By spotting diseases early, we can improve mango production, quality, and the livelihoods of farmers. This automated system offers a practical way to manage mango diseases in regions with similar climates.



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## 1. INTRODUCTION

Mangoes are more than just a popular fruit in Southeast Asia; they are a vital component of the agricultural economy. In countries like Bangladesh, mango production supports millions of livelihoods and plays a significant role in driving economic growth. However, this crucial sector faces significant challenges due to diseases that affect mango plants, leading to substantial losses in yield and quality. Addressing these challenges is essential for sustaining the economic and cultural importance of mango production. Agricultural diseases, particularly those affecting mango crops, can have devastating effects on both the local and global economy.

For instance, Saeed *et al.* [1] have identified *Lasiodiplodia theobromae* as the causative agent of mango dieback disease in the United Arab Emirates, with systemic fungicides like Cidely® Top showing promise for management. Khan *et al.* [2] employ laser induced breakdown spectroscopy (LIBS) to analyze elemental composition in mango pulp post-harvest, revealing qualitative and quantitative detection of organic and mineral elements, with implications for nutrition and health. Mia *et al.* [3] introduce a novel neural network ensemble (NNE) for mango leaf disease recognition (MLDR) that offers an efficient alternative, achieving 80% accuracy and potentially enhancing production. Kumari *et al.* [4] contribute valuable insights into mango disease management strategies, genetic identification, and disease dynamics, aiding in the enhancement of mango cultivation practices and ensuring sustainable production. Pham *et al.* [5] approached artificial neural network (ANN) approach that surpasses convolutional neural network (CNN) models in early disease detection, benefitting farmers with its potential for resource-constrained devices. Ismail *et al.* [6] uncovered *Lasiodiplodia* species, including *L. theobromae*, *L. egyptiacae*, and *L. pseudotheobromae*, in Egyptian mango plantations, emphasizing the necessity for taxonomic clarity and pathogenicity evaluation to guide disease control measures. Saleem *et al*. [7] utilized CNN to achieve 96.6% accuracy in classifying mango plant leaf photos, with a 90.83% detection rate using k-nearest neighbor (KNN) segmentation. They further improved accuracy to 90% by employing a two and nine clusters strategy for segmenting sick citrus leaf regions with optimal minimum bond parameters of 3%. Zhan *et al.* [8] identified *Fusarium proliferatum* from malformed mango seedlings in China, underscoring the importance of precise identification for disease understanding. This study contributes insights into *Fusarium* species linked to mango malformation.

Another approach addresses mango malformation disease (MMD) worldwide and mango sudden decline in Oman underscores the need for further research and vector management [9], [10]. Colina *et al*. [11] identified nine *Fusarium* species linked to MMD in Mexico, including the novel pathogen *F. mexicanum*, confirmed pathogenic through Koch's postulates. Shivakumar *et al.* [12] provide insights into mango postharvest management, focusing on preserving fruit quality and minimizing losses. Their review synthesizes research on innovative technologies aimed at enhancing mango quality throughout the supply chain. Trang *et al.* [13] introduce an image-based disease identification method using deep neural networks, achieving an 88.46% accuracy in identifying common mango diseases. This approach surpasses other pre-trained models, offering promise for efficient plant disease detection. Zainuri *et al.* [14] investigated potassium phosphonate and salicylic acid treatments for anthracnose control in mango fruit. While no effects were observed initially, salicylic acid treatments showed promise in reducing disease severity and slowing fruit ripening in subsequent seasons Gining *et al*. [15] addressing limitations in mango farming techniques, a disease recognition system using image processing offers practical benefits. Rahaman *et al.* [16] utilized machine learning techniques on mango fruit and leaf photos, achieving 97.81% accuracy with DenseNet169. Their Android app aids in disease identification and pesticide recommendation. Singh *et al.* [17] introduction of a multilayer convolutional neural network (MCNN) for diagnosing *Anthracnose* provides a promising solution for disease management. Rajbongshi *et al.* [18] address the crucial role of disease acknowledgment in enhancing harvest yield by employing CNNs, particularly DenseNet201, which achieves high accuracy (98.00%) in mango leaf disease classification, and streamlining detection methods. This research compilation by Plancarte *et al.* [19] provides comprehensive insights into various aspects of mango disease management and understanding. It explores the prevalence and genetic identification of malformation disease in Mexican mango nurseries, highlighting the critical need for pathogen-free planting material to curb disease spread during orchard establishment. Silimela and Korsten [20] evaluated the *Bacillus licheniformis* for controlling mango fruit diseases underscoring its potential in disease management, while Atinsky *et al.* [21] research on *Fusarium mangiferae* infection dynamics shed light on disease cycles and optimal conditions for fungal growth. Wongsila *et al.* [22] aim to design an algorithm for detecting anthracnose-infected mangoes showcasing promising advancements in disease detection technology. The proposal of an advanced alert system for disease outbreak forecasting by Jawade *et al*. [23] offers innovative solutions for timely disease management. Furthermore, investigations into chitosan and spermidine fruit coatings by Jongsri *et al.* [24] present practical approaches for enhancing post-harvest quality. A survey on nursery diseases in Bangladesh by Sarker *et al*. [25] provides insights into regional disease prevalence and efficacy of control measures. Finally, a comprehensive review of mango anthracnose contributes to improved disease control strategies.

This study aims to bridge this gap by developing an advanced machine learning-based system for the early detection and diagnosis of mango diseases in Bangladesh. By leveraging CNNs and other state-of-the-art deep learning techniques, the research seeks to accurately identify common mango diseases from images of leaves and fruits. This approach not only promises to enhance disease surveillance capabilities but also offers practical solutions to improve mango production practices. This research will involve several key steps. Initially, high-quality images of mango plants will be collected and preprocessed to enhance feature extraction. These images will then be analyzed using CNNs to identify disease patterns and classify them accurately. The system will be tested and validated against existing datasets to ensure its reliability and effectiveness. The ultimate goal is to provide a scalable and efficient tool that can be used by farmers and agricultural professionals in Bangladesh to mitigate the impact of mango diseases.

## 2. RESEARCH METHODOLOGY

Explaining the signs of many illnesses can be extremely similar, it can be very difficult to distinguish a healthy mango leaf or fruit from a diseased one just by looking at it. A suitable course of treatment cannot be started in such cases without a precise diagnosis. The farmers can lose a lot of money if it becomes infested with pests. We have decided to focus on this topic for our study as a result of these factors. An image-filtering model that converts correlations between quality ratings and irrelevant picture sources into correlations with a random forest algorithm may be created. They must be addressed before comparing them to additional machine learning model techniques to produce more methodically and result in a more effective deployment. To achieve our ultimate goal of reducing mango disease, we have experimented with a variety of different types of disease formats. The mango disease detection process is shown in Figure 1.

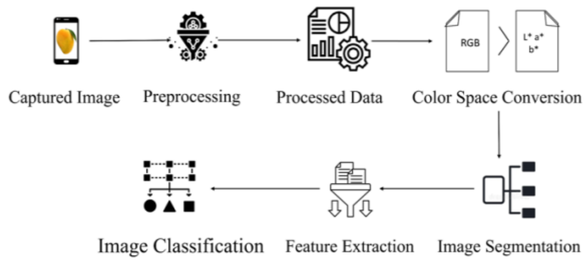



Figure 1. Mango disease detection process

## 2.1. Data collection

Flower disease, anthracnose/blossom blight, mango deformity, bacterial canker, leaf spot, stem end rot, dieback, twig blight, gummosis, bark splitting, bark scaling, and wilting mango sudden death syndrome (MSDS) were among the mango diseases we studied. These statistics were taken between March and July of 2023. Internet data is rarely gathered. Real-time data were collected in Rajshahi, Bangladesh.

## 2.2. Description of mango disease

Mango fruit includes a variety of phytochemicals, including polyphenols, ascorbic acid, and carotenoids, which have health-promoting qualities due to their antioxidant characteristics [12]. Fruit is the main usage of it. However, several diseases have an impact on its production. So, we found diseases there. The description and figure of different types of mango diseases are shown in Tables 1 to 4 and the healthy mango figure is shown in Figure 2. The edible head of a healthy mango should be white and look compact, with crisp, the color of healthy a mango and the leaves should be green. A mango that is in good health has no wrinkles, black stains, or imperfections.

Figure 2. Healthy mango

Table 1. Mango flower disease

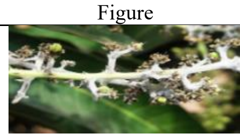
| Name | Disease description | Figure |
|---|---|---|
| Powdery mildew | The symptoms can be noticed on the inflorescence, the stalk of the inflorescence, the leaves, and the young fruits. One of the disease's distinguishing features is the superficial, powdery, white fungal growth in these areas. According to reports, the illness causes 20 to 80% crop loss. Conidia=9-32 °C and >25% R.H. Disease=10-31 °C with a relative humidity of 60-90%. |  |
| Anthracnose/ Blossom blight | Anthracnose is found in several parts of the mango tree. The first signs of the illness are blackish-brown patches on flowers and peduncles. Small black spots appear on panicles and open flowers, and as they grow larger, they damage the blossoms. Diseased blooms break off, leaving more persistent spikes on the peduncles, resulting in severe crop loss (10-90%).25-30 °C and 95-97% R.H. Overly nitrogenous. |  |
| Mango malformation | Despite being initially documented in India over a century ago (10, 14, 34), this disease was not discovered in Mexico until 1958 [11]. Recent research suggests that the sickness is caused by a fungus. Floral malformation (MF) and vegetative malformation (MV) are two different categories of symptoms that the workers have documented. |  |

Table 2. Mango leaf disease

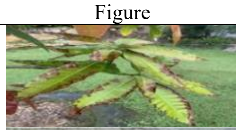
| Name | Disease description | Figure |
|---|---|---|
| Anthracnose | As symptoms, round or irregular dark to deep brown patches of varying sizes can be found on the leaf surface. In humid settings, the fungus multiplies rapidly. Young leaves attract more insects than older ones do. Attacks by insects may make it easier for pathogens to enter, leading to a high prevalence of disease. |  |
| Alternaria leaf spot | The condition begins with little, brownish circular spots on the surface of leaves. Later, the leaf lamina acquires a dense pattern of brown and black specks. The lower side of the leaves exhibits more pronounced symptoms. It is discovered that younger leaves are more prone than older ones. |  |
| Bacterial Canker | On leaves, the apex is generally densely packed with small, water-soaked, irregular to angular raised lesions. While younger leaves have more obvious and broader halos than older leaves, which can only be seen in bright sunlight, elder leaves have narrower halos. When a leaf is seriously affected, it becomes yellow and falls off. 25-30 °C and >90R.H. |  |

Table 3. Mango post-harvest disease

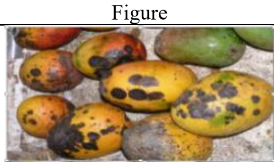
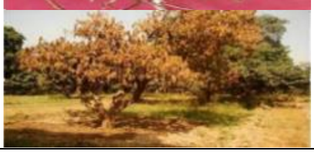
| Name | Disease description | Figure |
|---|---|---|
| Fruit anthracnose | The pre-harvest infection causes post-harvest rots. There are black patches in storage. Initially circular, the spots morph into large, uneven blotches that cover the entire fruit. The fungus rots the fruit deeply and causes massive, deep fractures in the areas. As a result, effective, safe, and affordable plant protection ways are integral [14]. |  |
| Stem end rot | As the fruit ripens, the stem end turns dark or black. Within two to three days, the entire fruit turns black, and the disease spreads downward, damaging half of the fruit's surface. Although the entire fruit typically has a blush, wrinkles are also noticeable. The afflicted skin remains solid, but rot develops in the pulp beneath. |  |

Table 4. Mango declines disorders disease

| Name | Disease description | Figure |
|---|---|---|
| Die back | Although the disease is visible throughout the year, it is distinguished by the top-to-bottom drying of twigs, particularly in elder trees, followed by leaf drying, giving the image of fire scorch. The upper leaves dry out and lose their color with time. The border rolls upward as the entire leaf dries. When such leaves shrink and fall off within a month. |  |
| Twig blight | The twigs develop elongated, dark, necrotic patches due to disease. The leaves gradually droop throughout the upswing before falling. Off The very young branches begin to dry from the tip down. Injuries, insect attacks, hot plants with weak roots, water stress, frost, and physical harm. |  |
| Gummosis | Gummosis affects 30-40% of young mango trees, particularly those planted in sandy soil, but it has been observed in other mango-growing conditions as well. The presence of enormous amounts of gum flowing from the surface of the damaged wood, the bark of the trunk, and on larger branches distinguishes the illness. |  |
| Barks cracking | The emergence of large, deep longitudinal fissures is a sign of bark cracking. Although the underlying wood is discovered to be significantly pitted, rooting is not connected to the fissures. Along with the fissures, gum pockets are also discernible. Later, as the bark dries and is taken off, it causes the consequences of girdling, yellowing, and leaf loss. |  |
| Root rot | Water-soaked patches that are circular to asymmetrical become infected at or below ground level. These patches grow in size, eventually encircling the entire stem base. In light of this, the diseased tissues begin to degenerate and become mushy, dark brown, or black. |  |
| Mango sudden death syndrome | Significant predisposing factors for this illness have been identified as improper watering and root damage. Mango trees with the condition wilt. Cankers may grow over vascular discoloration and discharge gum from the stem. Wilted leaves typically dry out and curl, although they remain attached to the tree for a few weeks. |  |

### 2.3. Image acquisition

The first phase of our approach is picture acquisition, in which we obtain example photos for training and testing. Images from a phone and a select handful from the internet were used in this research. The plants in the example photographs are both unaffected and sick. The mango image is taken with a phone camera and saved in digital media in a common digital format. The RGB format of these pictures.

### 2.4. Image preprocessing

Images gathered from multiple sources are referred to as raw pictures and cannot be used directly in the following phase. Aspects of image processing include improving and filtering the image, removing noise and undesired objects, and cropping the image to the desired size. Firstly, we apply image resizing which resizing the input image is critical for categorization. Images are reduced in size for additional processing. Then we apply image filtering which is a smoothing filter, for example, can remove noise from photographs. Finally, contrast enhancement is the process where histogram equalization is the method that is used to improve contrast. Images are improved to perform better.

### 2.5. Color conversion

Green represents mostly the healthy component of the plant; thus, we boost its value by 59%. Red and blue, on the other hand, must decrease in value by 30 and 11%, respectively. Thus, the conversion's equation is as follows: new grayscale image=$(0.3\times R)+(0.59\times G)+(0.11\times B)$. Figure 3 shows the color conversion in image preprocessing. The picture of the before color conversion and the after picture of after color conversion is shown in Figures 3(a) and 3(b).

(a) (b)

Figure 3. Color conversion in image preprocessing of (a) before and (b) after

### 2.6. Image segmentation

In this research, we used the k-means clustering technique to separate images into three groups. Using a set of criteria, analogous pixels are combined to categorize images into k groups. Its purpose is to reduce the total squared distance between the associated cluster and the training images. First, an RGB image had to be converted to L*a*b*, where L stands for the luminosity layer ("L*") and a*b* for the chromaticity layer. The Euclidean distance metric, which is shown as follows, is used to determine the distance once the image has been divided into three distinct groups. Where there are two-pixel coordinates (X1, Y1) and (X2, Y2), the Euclidean distance (d) is identical.

### 2.7. Feature extraction

Feature extraction is an important part of image analysis since it extracts significant information from images. Every disease, as we know, has distinguishing characteristics that help us comprehend it. Texture, form, and color are examples of these properties. The gray-level co-occurrence matrix (GLCM) was used in our study to examine five different forms of texture: contrast, energy, homogeneity, correlation, and entropy. The input image is also utilized to calculate the mean, standard deviation, variance, and kurtosis.

### 2.8. Classification

Using their collected features, the extracted classes of the images are classified using the image classification technique. Our suggested classification system has five classes: flower diseases, leaf diseases, fruit diseases/post-harvest diseases, decline disorders, and healthy. To classify our system, we, therefore, adopted a multiclass approach. In this topic, there are numerous classifiers available. We contrast a variety of classifiers, including random forest, IBK, K-Star, support vector machine, decision tree, and random forest. The accuracy of disease recognition is better (97.44%) with random forest, though.

### 2.9. Model study

The study focuses on classifying algorithms on the basis of accuracy. Each model discriminates by some method-instance-based learning, ensemble learning, or neural network. The goal is to establish which model is most reliable for classification purposes.

– K-Star: a slow, straightforward, and instance-based classifier is the K-Star model. Entropy measurement is the principal use of the K-Star algorithm. There are a lot of merits when utilizing entropy for gauging distance. Although we achieve a good classification accuracy of 86.08% with K-Star.
– Random committee: it is a supervised algorithm from the Meta group. The overall mean of the predictions generated by every base classifier is then applied to make the ultimate classification decision. The supervised learning method is much simpler, with an accuracy score of 80.40%.
– Instance-based algorithm (IBK): the IBK is another name for KNN. Euclidean distance matrix was employed. Here, the K value forecasts the number of closest neighbors based on the distance between them. The IBK provides 84.88% accuracy.
– Bagging: the bagging classifier is a meta-algorithm technique that the machine learning ensemble uses to generate classifiers for each sample of the training dataset. It is used in machine learning to check stability, increase accuracy, reduce variation, and prevent overfitting. The classifier provides 84.88% accuracy.
– Multilayer perceptron (MLP): the MLPs is combine hidden layers and the backpropagation method. MLP has been used by many academics since it functions better with numerical values. With this algorithm, the accuracy score is 88.40%.
– Randomizable filtered classifier: a basic filtered classifier adjustment showing the model with a randomizable filter acting as the main classifier. Each base classifier is built using a unique random number seed utilizing a randomizable filter classifier since it is an ensemble base classifier. The final outcome is established by averaging the predictions of each base classifier. The accuracy of this classifier is 81.52%.
– Multiclass classifier: when using 2-class classifiers to analyze multiclass datasets, the multiclass classifier is a Meta technique. This classifier can also apply error-correcting output codes. We get 83.76% accuracy using the multiclassClassifier algorithm.
– Support vector machine: support vector machine are supervised learning models with related learning algorithms that are used in machine learning to analyze data for regression and classification. The non-linear problem of classification could also be resolved with support vector machine with the use of kernel functions which transform the information that arrives into a space with more dimensions. The accuracy score using this algorithm is 94.80%.
– Random forest: traditional machine learning uses the supervised random forest algorithm. It uses learning based on decision trees. Because it can handle both categorical and numerical data, it is a strong classifier. The random forest method is simple enough for humans to understand. The ultimate result for illness identification is determined by the highest number of votes received from each decision tree node. Compared to other classifiers, this one has a higher accuracy score of 97.44%.
– PART: a rules-based classifier is a PART. In this rules-based classifier, class prediction is done using association rules among all the attributes. These precise forecasts are regarded as coverage. They have the capacity to forecast more than one conclusion. The accuracy of this classifier is 78.76%.

## 3. RESULTS AND ANALYSIS

500 photos of various mango illnesses are collected from Rajshahi, Bangladesh for our experimental investigation, and additional images are collected online. For each of the following categories: powdery mildew, anthracnose/blossom blight, mango deformity, leaf diseases, fruit diseases, decline disorders, and healthy images, the picture database includes 100 images. Images that have been acquired are pre-processed using techniques including noise reduction, contrast enhancement, and filtering. Euclidean distance metrics and k-means clustering are used to segment images. 10 features are then taken from the image and saved for later analysis. There are no longer any unnecessary features. This allows the diseases to be identified and categorized using random forest. The step-by-step mango disease detection process analysis is shown in Table 5. The random forest method produced the highest accuracy (97.44%) in this analysis and performance of random forest classifier is shown in Table 6. The comparison of the other classifiers is shown in Figure 4. In earlier studies, researchers attempted to create a unique model to identify particular diseases like only leaf disease or only fruit diseases [3], [5], [16]–[19]. But in this research, we tried to detect a higher number of mango diseases (like leaf diseases, fruit diseases, and others) using machine learning and get good accuracy.

Table 5. Step by step mango disease detection process analysis

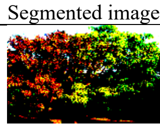
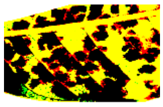
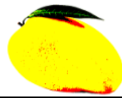
| Original image | Resized image | Contrast-enhanced image | Segmented image | Type |
|---|---|---|---|---|
|  |  |  |  | Decline diseases |
|  |  |  |  | Post-harvest disease |
|  |  |  |  | Leaf diseases |
|  |  |  |  | Flower disease |
|  |  |  |  | Healthy mango |

Table 6. Performance of random forest classifier

| Type | Precision (%) | Specificity (%) | Sensitivity (%) | FNR (%) | FPR (%) | Accuracy (%) | Avg. accuracy (%) |
|---|---|---|---|---|---|---|---|
| Flower diseases | 93.00 | 98.25 | 93.00 | 7.00 | 1.75 | 97.20 | |
| Leaf diseases | 93.81 | 98.50 | 91.00 | 9.00 | 1.50 | 97.00 | |
| Post harvest diseases | 92.16 | 98.00 | 94.00 | 6.00 | 2.00 | 97.20 | 97.44 |
| Decline disorders | 95.15 | 98.75 | 98.00 | 2.00 | 1.25 | 98.60 | |
| Healthy mango | 93.88 | 98.50 | 92.00 | 8.00 | 1.50 | 97.20 | |

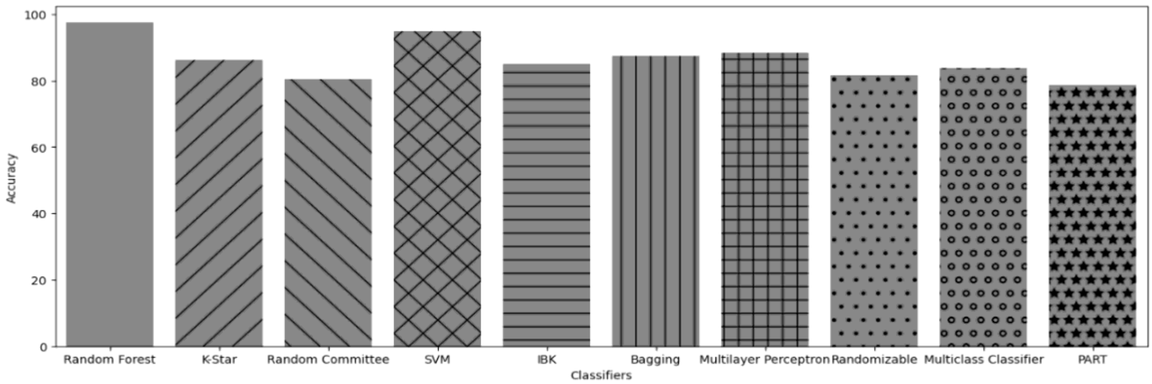



Figure 4. Comparison of the other classifiers

## 4. CONCLUSION

Bangladesh leads the way in pioneering automatic mango disease recognition, coupling it with data mining techniques to forecast crop yields based on climate inputs. This innovative system aims to accurately identify various mango ailments, including decline disorders, fruit, post-harvest, leaf, and flower diseases, as well as healthy mango fruit. Commencing post-photo capture, the process involves essential preprocessing steps, such as image resizing, contrast enhancement, and RGB color scheme adjustment. Picture segmentation, facilitated by Euclidean distance and k-means clustering, precedes feature extraction utilizing two sets of GLCM features, totaling 10 attributes. These extracted features power data classification, resulting in an impressive average accuracy rate of 97.44% for illness identification. This integrated approach signifies a significant leap forward in mango disease management, promising improved crop health and yield predictions.

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**AUTHOR CONTRIBUTIONS STATEMENT**

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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| Abdus Sattar | ✓ | | | | ✓ | | | | | ✓ | | ✓ | ✓ | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

**CONFLICT OF INTEREST STATEMENT**

All author hereby states that no financial, personal, professional, political, ideological, or religious interests exists that could have influenced the research analysis, or interpretation of the data presented herein. Competing interests if any have been disclosed by all authors, and none impede the impartially of this work.

**DATA AVAILABILITY**

The data that support the findings of this study are available from the corresponding author, [MAAR], upon reasonable request. The data are not publicly available due to privacy concerns and institutional policy restrictions regarding the handling of sensitive or personally identifiable information.

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