Date Fruit Classification with Machine Learning and Explainable Artificial Intelligence

Md. Sahidullah
Undergraduate Student, Department of CSE
Asian University of
Bangladesh

Nasim Mahmud Nayan
Undergraduate Student, Department of CSE
University of Information
Technology and Sciences

Md. Samin Morshed
Project Coordinator, Digital Services
IoT and VAS
Robi Axiata Limited

Mohammad Mobarak Hossain
Associate Professor, Department of CSE
University of Information
Technology and Sciences

Muhammad Usama Islam
Lecturer, Department of CSE
Asian University of
Bangladesh

ABSTRACT

Fruit research now has reached a new dimension thanks to machine learning, which produces actionable insights for further exploration by practitioners in the agricultural domain. In order to automatically categorize the edibility of date fruit, we investigated various types of date fruits and used explainable artificial intelligence (XAI) techniques combined with machine learning-based methods to effectively classify and explain the classification task. Our result shows that with a formidable accuracy ranging within the 90-92 percentile for seven methods, including boosting, bagging, support vector machine (SVM), k-nearest neighbor (KNN), and MLPs, the machine learning methods combined with Local Interpretable Model-Agnostic Explanations (LIME) based XAI provides better actionable insights which can be utilized by domain experts and stakeholders to produce and supply quality fruits particularly date fruits thus contributing in broader perspectives with respect to this dynamically evolving domain. The implementation of the investigation and experiment is available in Github. [1]

General Terms

Agriculture, Explainable Artificial Intelligence

Keywords

Agriculture, Machine Learning, Intelligent Farming, Explainable Artificial Intelligence, Ensemble Methods

1. INTRODUCTION

Daily population growth adds to the pressure on the agricultural industry. There are significant losses throughout the entire agricultural process, from crop selection to product sale. Farming-related issues may be resolved and better decisions made by farmers if they keep track of information about the crops, environment, and market. Information can be collected and processed using technologies like blockchain, IoT, machine learning, deep learning, cloud computing, and edge computing. The use of computer vision, machine learning, and IoT applications will help raise production, enhance quality, and ultimately increase the profitability of farmers and related industries. To increase the overall harvest yield, precision learning is crucial in the field of agriculture [18]. 30 to 35 percentile of the harvested fruit is wasted because there aren't enough skilled workers. A crucial role for machine learning is played in the food and fruit systems. Fruit identification systems have been applied in many real-world scenarios, such as store checkouts, where they may be used in place of manual scanner tags. Recognizing various fruit varieties is a repetitive task in supermarkets, where the cashier must define each item's type to determine its price. The ideal solution to this issue is a fruit and vegetable recognition system that automates labeling and price calculation. This section provides examples of how various researchers are approaching the problem of automatic fruit identification[4]. Fruit's exterior quality is typically evaluated by looking at its color, texture, size, shape, and visual flaws. Local Binary Pattern (LBP) and common fruit characteristics, such as color, size, shape, and texture, are discussed. Artificial neural networks (ANN), convolutional neural networks (CNN), K-nearest neighbor (KNN), and support vector machines (SVM) are effective machine learning algorithms that can be used for fruit classification tasks [10]. Automatic fruit classification for ten different types of fruit—apple, dates, blueberries, grapes, peach, pomegranate, watermelon, banana, orange, and mango—is successfully introduced by Jasmeen Gill and her team using soft computing techniques [8].We discovered that some models did not produce the desired results because their data was varied in nature, gathered from various sources, at various growth stages, and under various lighting conditions. Currently, some researchers are testing XAI and its usage in interpretable domain [13]. The remainder of the paper is organized as follows. The related works of fruit-based classification, particularly date fruits and the most recent develop-

[1]Code implementation

ments in date fruit detection are examined in Section 2. Our suggested approach and methodology are briefly explained in Section 3. Section 4 discusses our implementation and results analysis as well as XAI-based explanation through LIME before concluding. The conclusion and future scope of this work are contained in Section 5.

2. LITERATURE REVIEW

Image classification for determining objects has come a long way since its inception. Fruit classification is one among many fields where the techniques of image classification have been used to make things easier. We can use state of the art Machine learning techniques to perfectly classify fruits with minimum error. In this paper we are dealing with the efficiency as well as the precision of the accuracy for the date fruit, a common fruit found abundant in the gulf region.

In [17], the authors uses a very well known traditional method to classify fruits. For classification, this paper makes use of color and texture feature of the fruits. The classification is done by Support Vector Machine (SVM) classifier which has achieved the accuracy of 95.3%. The SVM works on features derived from statistical as well as co-occurrence ones.

Alzu'bi et al [2] have made classification on date fruit, which this paper works on. This paper classifies the quality of date fruit with SVM. A hue saturation matrix is derived from the thresholding. By calculating that matrix, the coloration and color frequency is derived and compared with Agrexco color table. This by classifying color of dates, the edibility can be confirmed.

Astuti et al [3] also makes use of SVM in their fruit classification experiment as well. They made a comparative analysis on SVM and Artificial neural network analysis on the same task. In their experimentation, the feature is extracted via FFT. Eventually this paper shows that SVM technique is more efficient and accurate, which our paper makes use of.

In [11], The authors used deep learning methods to identify fruits. Here, the authors make a comprehensive analysis on fruit recognition and evaluation when it comes to Convolutional Neural Networks(CNN). A few well known models are used here, a few of them being VGG16 and AlexNet.

We can see that in [7] paper proposes fruit classification model which juxtaposes the usage of CNN, LSTM and RNN, and combines them to create a hybrid model. It also heavily focuses on image enhancing techniques like type II fuzzy logic based system, as it is a crucial part of this paper's experimentation. The CNN and RNN combination helps speed up the calculation of the relation between hierarchical labels; along with LSTM to counter the gradient problems.

In classification of another kind of fruit, banana, this paper [21], classifies it by using CNN. The features extracted from the CNN are then moved forward and fed to the random forest as well as KNN classifiers.

Gunning's team [9] described a segment on XAI, the authors focus on explaining and broadening on the topic of Explainable Artificial Intelligence(XAI) and its importance on how it could provide with precision and elaboration of the expected result, within the users' context of course. For example, SVM is widely successful in creating an internal representation of a model. But what it gains in performance, lacks even more in explanation. XAI aims to relieve that [13]. Because, almost most the time the most accurate models are the least explainable.

Moreover, in [6], the authors explain a comparative analysis among the visual features and classifiers when it comes to fruit classification problem. They have talked about six classifiers, which are SVM, KNN, NB, DT, LDA and BPNN as well as they have described broadly their accuracies and nuances when it comes to fruit classification. They come to the conclusion that SVM and neural networks have an edge when there are more number of features to be analyzed.

Koklu and his team [15] used image processing techniques to provide several features for date fruit processing from images. Our work in fact picks up from here and paces onto utilizing efficient machine learning techniques amalgamated with effective XAI to provide a foreward for this agricultural based research work.

3. PROPOSED APPROACH

The dataset that we utilized for our work was taken from the research work of Koklu and his team [15]. The procedure of our proposed endeavor included understanding the dataset through dataset description and exploratory data analysis. Insights revealed from our endeavor added the tasks of standard data cleaning and missing value handling from where the data was label encoded and standardized for further manipulation.

3.1 Dataset Description

The dataset revealed pertinent information about the dataset. The dataset included 34 features of attributes in the dataset including the class label whereas, the class labels were of 7 kinds as depicted in figure 1 thus making the classification task a multi-class classification. The dataset had 898 rows in total and our experimentation was split into standard 80-20 split of train and test data values. So, the training dataset of our experimentation would have 718 rows and we would test our result on 180 data.

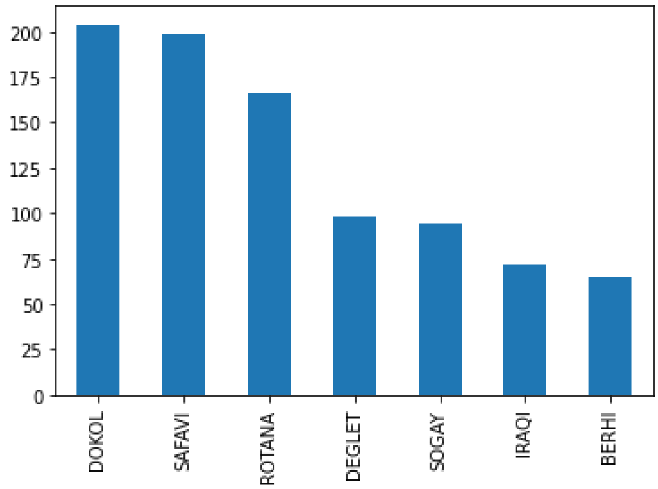

Fig. 1. Available classes of our dataset

3.2 Exploratory Data Analysis

A significant amount of exploratory data analysis (EDA) was done to comprehend the nature of the dataset. We begin by using our codebase to treat the missing values before encoding the categorical and non-categorical values to fit classification tasks. According to the dataset, our EDA shows that the dokol datefruit has the highest amount of dates (200+), followed by the safavi dates (190+), the

deglet dates (100+), the sogai dates (90+), the iraqi dates (75+), and the berhi dates (70+). Based on the different types of date fruit, figure 1 gives an overview of date fruit classes that were used in our experiment.
The data that needed label encoding were encoded to produce numercial data types and at the very last all data were standardized for ease of processing in our experimentation using scikit-learn [20]. For the standardization, the standard score of a sample x is shown in equation 1 through calculating ζ.

$$\zeta = \frac{x - \mu}{SD} \tag{1}$$

where, μ denotes the mean value as depicted in equation 2 and SD stands for standard deviation as shown in equation 3.

$$\mu = \frac{1}{M}\sum_{n=1}^{M}(x_n) \tag{2}$$

$$SD = \sqrt{\frac{1}{M}\sum_{n=1}^{M}(x_n - \mu)^2} \tag{3}$$

3.3 Materials and Methods

Several machine learning (ML) techniques were used in the experiment.
Some ensemble methods that included boosting and bagging methods were also included in our experimentation. A total of 7 machine-learning methods were utilized in our experiment. The methods constitute including category boosting (CatBoost), extreme gradient boosting (XGBoost), support vector machine (SVM), k nearest neighbor (KNN), multi-layer perceptron (MLP), logistic regression (LR), and bagging methods. These techniques were chosen due to their well-known effectiveness in classification tasks in the machine learning and supervised learning domains [16].
We used the confusion matrix to determine the evaluation process and used relevant scikit-learn libraries for determining accuracy, precision, recall, and F1-score [22, 5] for our classification task. The rationale that we used for selecting other evaluation metrics other than accuracy is because of its in-accurateness in providing the real result in case of imbalanced dataset. Hence, F1-score and Mathews Matthews correlation coefficient (MCC) [5], instead were used. The reliability of MCC in our opinion is widely accepted since it only produces a high score if the prediction obtained good results in all of the four confusion matrix categories. The equation for F1 score is depicted in equation 4 and MCC is shown in equation 5.

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \tag{4}$$

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{5}$$

Furthermore, another important well known statistic for measuring the performance is Cohen's kappa [1], who's equation is provided in equation 6.

$$C_k = \frac{Accuracy - P_e}{1 - P_e} \tag{6}$$

Last but not the least, we have also added a loss measure named hamming loss which provides the fraction of the incorrect labels to the total number of labels [1]. The formula for hamming loss is provided in equation 7.

$$H_l = \frac{1}{m}\sum_{i=1}^{m}\frac{|y_i \Delta y_i^1|}{Q} \tag{7}$$

The error rates that we have used in our experiment was mean square error (MSE), root-mean-square error (RMSE), mean absolute error (MAE), and mean squared logarithmic error (MSLE) [14]. For the ith sample, Squared Logarithmic Error (SLE) is calculated as $SLE = (log(P+1) - log(A+1))^2$, where P stands for prediction and A stands for actual result. MSLE is then calculated as $\mu(SLE)$ where μ is the mean. it is interesting to note the usage of +1 in the calculation to avoid obtaining the logarithm of 0. As for MSE and MAE, the equation for MSE is given in equation 8, and MAE in equation 9. RMSE is calculated as $\sqrt{MSE}$ by taking the squared-root over the MSE value obtained from equation 8.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{9}$$

For explanation and visualization purposes after obtaining results, we used a local surrogate models specifically Local Interpretable Model-Agnostic Explanations (LIME) [19] for our work.
Mathematically, local surrogate models with interpretability constraint can be recorded as an explanation function E(x) that is defined below in equation 10.

$$E(x) = argmin_{g \in G} L(f, g, \pi_x) + \Omega(g) \tag{10}$$

With solid background in our theoretical research, the next section discusses the results that we obtained from our experiment and the implications that it might have for future practitioners in this domain.

4. EXPERIMENTATION AND RESULTS

All of the experiments' results are visible to us. Figure 2 shows a comparison of the experimental models' levels of accuracy. We observe a formidable accuracy depicted by all of the machine learning models. We observe that boosting methods are performing well under the aforementioned circumstances with an accuracy of 87% for XGBoost model whereas CatBoost performed slightly better with an accuracy of 90%. Both SVM and Bagging methods performed well with an accuracy of 91% but the clear winner was MLP and LR with an accuracy of 92% as depicted in figure 2. Table 4 provides the detailed inscription of the precision, recalls, and F-1 score comparisons of the tested methods. The confusion matrix for the best model, which in our experiment is MLP, is shown in figure 3.
Table 4 shows that MLP is a decisive winner in this category as well, with an astounding perfect score in every category, including precision, recall, and F1-Score. Thus, there are now two observations, and we can confidently conclude that MLP is the best model to accompany it.
Figure 3 depicts the MLP model's confusion matrix. Here, we can see that true negatives and true positives are overwhelmingly accurate. In fact, the aforementioned tables and figures were indeed

Table 1. Table listing the average precision, average recall, and average F1-score of the experiment

Ml Method	P_{avg}	R_{avg}	$F-1_{avg}$
CatBoost	0.854	0.851	0.85
XGBoost	0.822	0.82	0.818
Bagging	0.898	0.877	0.884
LR	0.91	0.888	0.895
SVM	884	0.891	0.885
KNN	0.845	0.841	0.842
MLP	0.905	0.895	0.9

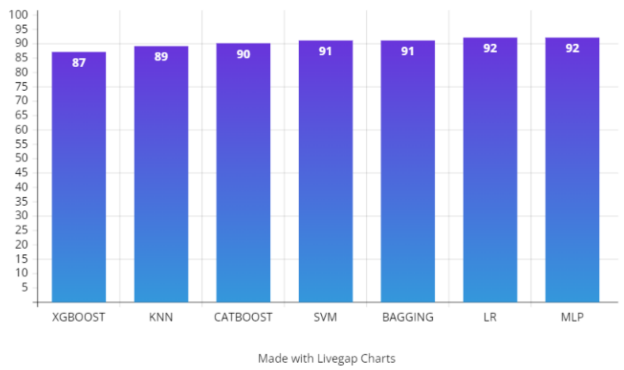

Fig. 2. Accuracy comparison of experimented models

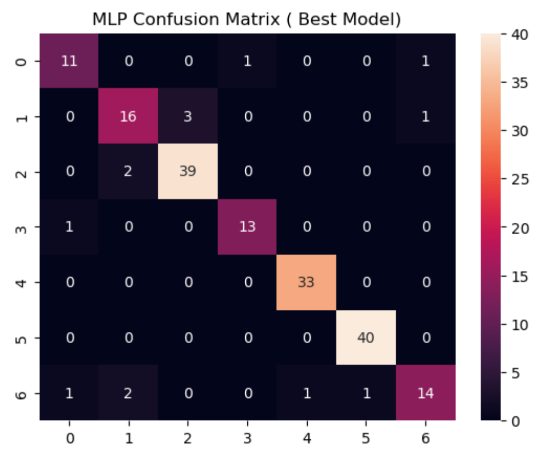

Fig. 3. Confusion matrix of best model (MLP)

derived from the confusion matrix as depicted in this figure 3 for MLP.

Several error rates were also noted in our experiment to provide a proper visualization to the readers about to what extent and magnitude the error was observed. Table 2 lists the numerical values of error rates MSE, MSLE, MAE and RMSE that was obtained from our experiment. As discussed in proposed approach and materials and methods, we realized that accuracy alone can not be a good evaluation measure which is why we observed other measures such as precision, recall and f1-score. However, MCC score was also calculated along with cohen's kappa score as well as hamming loss to realize the robustness of several statistic along the way. Table 2 provides the MCC, C_k value and H_l values of our results.

4.1 LIME Visualization

XAI has played an enormous role in visualizing the black box models thus making models interpretable [13, 12]. Figure 4 takes the first test-data of the experimented models and provides an explanation based on features assumed importance to provide the decision as to why the test data has been mapped to class 1 in this case. We vividly see the contribution of several features that led to the decision in this case through the LIME visualization.

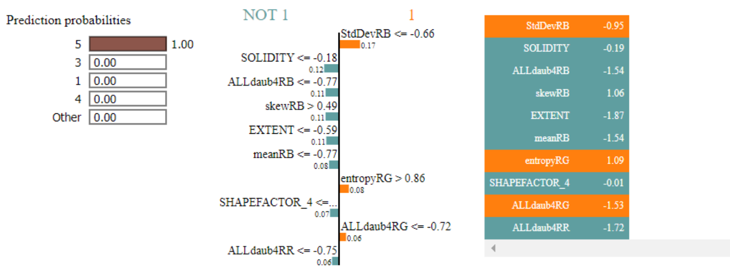

Fig. 4. LIME explanation from first test-data instance of MLP

5. CONCLUSION

The potential for machine learning in the agricultural sector is enormous and it will only continue to grow every day. The edibility of various date fruits from various regions was determined in this paper. This study places a lot of emphasis on the necessity of both on the power of machine learning and the explainability principles of black box models in order to achieve our goals. In this paper, the comparative analysis of different experimental models in date fruit classification is given with a clear winner, which is MLP. But there is scope to make further improvements, as we can see from the error evaluations. Further research into MLP is needed in order to increase accuracy. Also, this paper emphasizes greatly on the interpretation of the models, and thus LIME and XAI come into play when explaining why a model works and classifies test data into a particular class. Even though the LIME implementation was accurate in this paper, more could be done by performing every model and explaining them in the same way for more insights as well as to understand the accuracy of the cases for each model. Thus it can be interpreted that this experiment was a success with a lot of future prospects.

Table 2. Table listing the error rates as well as the the MCC, Cohen's kappa and Hamming loss values of the experiment

ML Method	MSE	MSLE	MAE	RMSE	**MCC**	C_k	H_l
CatBoost	0.988	0.109	0.277	0.994	0.866	0.866	0.111
XGBoost	1.172	0.152	0.327	1.082	0.846	0.845	0.127
Bagging	0.922	0.099	0.233	0.960	0.893	0.892	0.088
LR	0.916	0.090	0.227	0.957	0.906	0.905	0.077
SVM	0.8	0.085	0.222	0.894	0.887	0.886	0.094
KNN	1.288	0.153	0.322	1.135	0.866	0.866	0.111
MLP	0.972	0.094	0.227	0.986	0.906	0.906	0.077

6. REFERENCES

[1] Shadi Alzu'bi, Omar Badarneh, Bilal Hawashin, Mahmoud Al-Ayyoub, Nouh Alhindawi, and Yaser Jararweh. Multi-label emotion classification for arabic tweets. In *2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS)*, pages 499–504. IEEE, 2019.

[2] Reem Alzu'bi, A Anushya, Ebtisam Hamed, Eng Abdelnour Al Sha'ar, and BS Angela Vincy. Dates fruits classification using svm. In *AIP Conference Proceedings*, volume 1952, page 020078. AIP Publishing LLC, 2018.

[3] Winda Astuti, Satrio Dewanto, Khristian Edi Nugroho Soebandrija, and Sofyan Tan. Automatic fruit classification using support vector machines: a comparison with artificial neural network. In *IOP Conference Series: Earth and Environmental Science*, volume 195, page 012047. IOP Publishing, 2018.

[4] Santi Kumari Behera, Amiya Kumar Rath, Abhijeet Mahapatra, and Prabira Kumar Sethy. Identification, classification & grading of fruits using machine learning & computer intelligence: a review. *Journal of Ambient Intelligence and Humanized Computing*, pages 1–11, 2020.

[5] Davide Chicco and Giuseppe Jurman. The advantages of the matthews correlation coefficient (mcc) over f1 score and accuracy in binary classification evaluation. *BMC genomics*, 21(1):1–13, 2020.

[6] Sumaira Ghazal, Waqar S Qureshi, Umar S Khan, Javaid Iqbal, Nasir Rashid, and Mohsin I Tiwana. Analysis of visual features and classifiers for fruit classification problem. *Computers and Electronics in Agriculture*, 187:106267, 2021.

[7] Harmandeep Singh Gill and Baljit Singh Khehra. Hybrid classifier model for fruit classification. *Multimedia Tools and Applications*, 80(18):27495–27530, 2021.

[8] Jasmeen Gill, Parvinder Singh Sandhu, Tejwant Singh, et al. A review of automatic fruit classification using soft computing techniques. In *Int. Conf. Comput. Syst. Electron. Eng*, pages 91–98, 2014.

[9] David Gunning, Mark Stefik, Jaesik Choi, Timothy Miller, Simone Stumpf, and Guang-Zhong Yang. Xai—explainable artificial intelligence. *Science robotics*, 4(37):eaay7120, 2019.

[10] Anuj Gupta, Mr Rishi Kushwaha, and Mr Kailash Patidar. A survey: Fruit classification using machine learning. *International Journal of Engineering Technology and Applied Science*, 5(7), 2019.

[11] DNVSLS Indira, Jyothi Goddu, Baisani Indraja, Vijaya Madhavi Lakshmi Challa, and Bezawada Manasa. A review on fruit recognition and feature evaluation using cnn. *Materials Today: Proceedings*, 2021.

[12] Muhammad Usama Islam and Beenish Moalla Chaudhry. A framework to enhance user experience of older adults with speech-based intelligent personal assistants. *IEEE Access*, 11:16683–16699, 2023.

[13] Muhammad Usama Islam, Mozaharul Mottalib, Mehedi Hassan, Zubair Ibne Alam, SM Zobaed, Fazle Rabby, et al. The past, present, and prospective future of xai: A comprehensive review. *Explainable Artificial Intelligence for Cyber Security*, pages 1–29, 2022.

[14] Md Karim, Md Foysal, Sunanda Das, et al. Stock price prediction using bi-lstm and gru-based hybrid deep learning approach. In *Proceedings of Third Doctoral Symposium on Computational Intelligence*, pages 701–711. Springer, 2023.

[15] Murat Koklu, Ramazan Kursun, Yavuz Selim Taspinar, and Ilkay Cinar. Classification of date fruits into genetic varieties using image analysis. *Mathematical Problems in Engineering*, 2021, 2021.

[16] Sotiris B Kotsiantis, Ioannis Zaharakis, P Pintelas, et al. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1):3–24, 2007.

[17] R Shantha Selva Kumari and V Gomathy. Fruit classification using statistical features in svm classifier. In *2018 4th International Conference on Electrical Energy Systems (ICEES)*, pages 526–529. IEEE, 2018.

[18] Vishal Meshram, Kailas Patil, Vidula Meshram, Dinesh Hanchate, and SD Ramkteke. Machine learning in agriculture domain: A state-of-art survey. *Artificial Intelligence in the Life Sciences*, 1:100010, 2021.

[19] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. " why should i trust you?" explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1135–1144, 2016.

[20] Sklearn Preprocessing StandardScaler—Scikit-Learn. 0.24. 2 documentation.

[21] M Vijayalakshmi and V Joseph Peter. Cnn based approach for identifying banana species from fruits. *International Journal of Information Technology*, 13(1):27–32, 2021.

[22] Ni Wayan Surya Wardhani, Masithoh Yessi Rochayani, Atiek Iriany, Agus Dwi Sulistyono, and Prayudi Lestantyo. Cross-validation metrics for evaluating classification performance on imbalanced data. In *2019 international conference on computer, control, informatics and its applications (IC3INA)*, pages 14–18. IEEE, 2019.