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Hyperspectral image construction in different spectral bands of tea leafs for identifying the tea type using O-ConvNet-RF model

Likitha Gongalla, Monali Bordoloi
School of Computer Science and Engineering, VIT-AP University, Amaravati, India

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ABSTRACT

Tea, a commonly consumed beverage, is susceptible to being sold in adulterated or expired forms by third-party vendors. Hyperspectral imaging across different wavelength bands has proven to precisely assess the diverse types of tea and their corresponding financial gains. This study aims to employ a deep learning methodology in conjunction with hyperspectral imaging for efficiently classifying tea leaves. A novel approach is proposed, wherein a waveband convolutional neural network is utilized to generate hyper spectral images of tea leaf samples with enhanced resolution. The model known as optimized-convolutional neural network-random forest O-(ConvNet-RF) demonstrated exceptional performance, achieving high accuracy, impressive recall, F1 score, and notable sensitivity rate, outperforming existing alternative methods. The tea leaf types, namely green, yellow, and black, were accurately identified using a combination of the random forest (RF) model and the O-ConvNet-RF model. The tree-based classification method for the identification of tea leaves demonstrated superior performance as compared to alternative machine learning models. In general, this study presents a successful methodology for the classification of tea leaves, with potential implications for consumer processing and distributor profit analysis.

Corresponding Author:

Likitha Gongalla
School of Computer Science and Engineering, VIT-AP University
Amaravati, India
Email: ankithareddy032@gmail.com

1. INTRODUCTION

The beverage commonly referred to as tea, which is scientifically identified as Camellia Sinensis, is widely consumed and has been acknowledged for its medicinal and health-promoting properties. In recent years, there has been an upward trend in global tea production [1], [2]. The production of tea encompasses a range of tea varieties derived from distinct tea plant species and subjected to various processing techniques, resulting in a wide array of quality criteria. The precise evaluation of tea quality holds significant importance within the tea production process. In the conventional practice, tea quality is assessed by skilled tea tasters through the examination of sensory attributes including aroma, color, texture, and morphology [3], [4]. However, it is important to note that individual perceptions can often be subjective and inconsistent as a result of a multitude of factors.

The main objective of this study is to investigate the potential of hyperspectral imaging in the identification of various tea types in both freshly harvested and fermented tea leaves. The study's specific objectives are outlined as follows: i) identification of the fragrance and taste of tea leaves for initial screening of tea class prediction using artificial sensor pre-processing; ii) capturing hyperspectral images of both fresh tea leaves and fermented samples to improve the identification and examination of tea leaf properties; and

iii) development of a processing technique to quantitatively determine the quality and variety of tea by utilizing images taken at the most suitable wavelength bands.

The remaining part of the research work is organized as follows. In section 2 a survey of the existing works is presented. A detailed discussion of the proposed work is presented in section 3. Results and discussion are elaborated in section 4. At last, section 5 draws some conclusions about the work done.

2. LITERATURE SURVEY

In recent years, spectroscopic technology has been harnessed in several studies for the identification of tea leaves. Utilizing three distinct visible and near-infrared (Vis/NIR) spectroscopic measures, namely interactance, reflectance, and transmittance, researchers were able to swiftly detect varying degrees of internal insect infestation in tea leaves [5]-[7]. To evaluate the efficacy of each method in predicting the soluble solids content (SSC) of tea leaves, researchers focused on interactance and transmission measurements using Vis/NIR spectroscopy. This method holds particular interest because of its robustness in identifying a wide range of agricultural and related commodities [8], [9].

In recent years, several investigations have employed hyperspectral imaging techniques. However, there has been limited work conducted thus far in the identification of features such as location and area information in fresh, oxidized, and fermented tea leaves using hyperspectral imaging [10], [11]. Table 1 provides details of several research works in the field of tea type classification that motivate the work of the proposed model of this paper.

Table 1. Existing research works for tea-type classification

Researchers	Instruments used and research field	Classification categories	Methods and results
(Wang et al. [12], 2021)	NIR spectrometer, tea types classification.	4 types of tea: black, green, yellow, and oolong tea.	Nonlinear radial basis function-support vector machine (RBF-SVM): 96.3%
(Cardoso and Poppi [13], 2021)	NIR spectroscopy, tea blends classification.	4 kinds of green tea blends.	Support vector machines (SVM): 93%
(Firmani *et al.* [14], 2019)	NIR spectroscopy, tea brands classification.	3 brands of tea: Darjeeling, Ceylon, and English breakfast.	Partial least square-discriminant analysis (PLS-DA): 95.57%
(Li *et al.* [15], 2021)	Smartphone imaging coupled with micro-near-infrared spectrometer, tea grades classification.	7 quality grades of Keemun black tea.	SVM: 94.29%.
(Zhuang *et al.* [16], 2019)	NIR spectroscopy, tea geographical origin classification.	2 geographical origins of Shandong, China green tea.	Multi-wavelength statistical discriminant analysis (MW-SDA): 96.3%.

3. PROPOSED METHOD

The manual evaluation of tea leaf quality traditionally relied on experts who assessed factors such as color, aroma, taste, and thickness. In this proposed approach, the system utilizes electronic nose and tongue sensors to initially evaluate tea leaf samples, determining their class type [17]. Subsequently, hyperspectral images of the tea leaves are collected using a hyperspectral image spectrograph (HIS) across different wavebands. These images are then analyzed using an optimal convolutional neural network (CNN), enabling the evaluation of tea leaf quality in the second stage, leading to improved tea categorization [18]. This methodology not only benefits the tea production industry in India but also promotes consumer health by ensuring the consumption of high-quality tea [19].

To overcome the limitations of electronic sensors, a second level of processing is introduced using image spectrograph technology. Hyperspectral images of the tea leaves are collected and processed using deep learning techniques to identify the tea category type [20]. A tea leaf recognition model is developed utilizing a CNN model, and the classification of tea leaves is performed based on their extracted features, employing a random forest (RF) classification model [21]. This comprehensive methodology enhances the accuracy and efficiency of tea leaf classification and contributes to the advancement of tea quality evaluation techniques.

The proposed methodology comprises distinct levels of tea leaf processing, as depicted in Figure 1, aimed at achieving precise tea leaf predictions. This approach is designed to enhance the quality identification for consumers' requirements and increase profits for vendors. Significantly, the proposed methodology is highly efficient, completing the entire process of accurately identifying tea types in minimal time. It involves the utilization of a hyperspectral imaging system to capture images of tea leaves, which are subsequently processed using deep learning techniques to construct both a tea recognition model and a classification model.

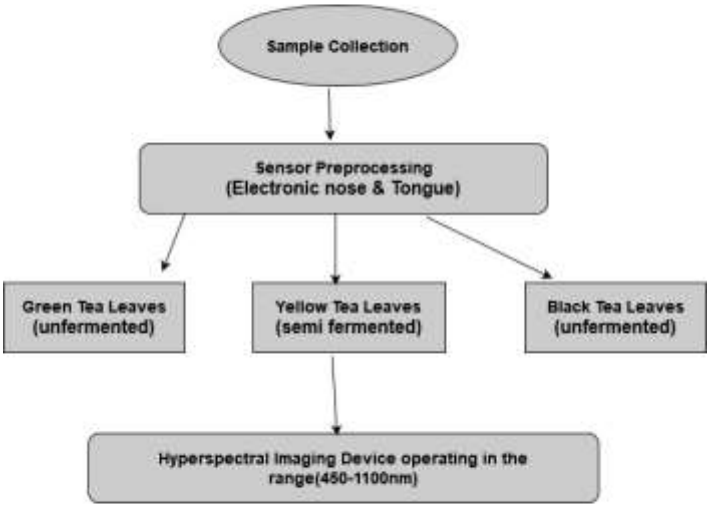

Figure 1. Level-1 proposed methodology of hyperspectral image collection of tea leave samples

Tea polyphenols present in the tea leaves are calculated from (1) as:

$$T_P = \frac{x - y \times w \times 0.00582/0.318}{v \times U1/U2} \quad (1)$$

Figure 2 proposes the methodology in detail. In (1), 'T_p' represents the total polyphenols present in the collected samples, and the 'U1', 'U2' represent the volume of the test solution in milliLiters (mL) and the 'x' represents the total potassium permanganate present in the polyphenol and the 'y' represents the potassium permanganate present in the blank. The 'v' represents the total mass of the tea leaves sample and the 'w' represents the weight of the potassium permanganate concentration.

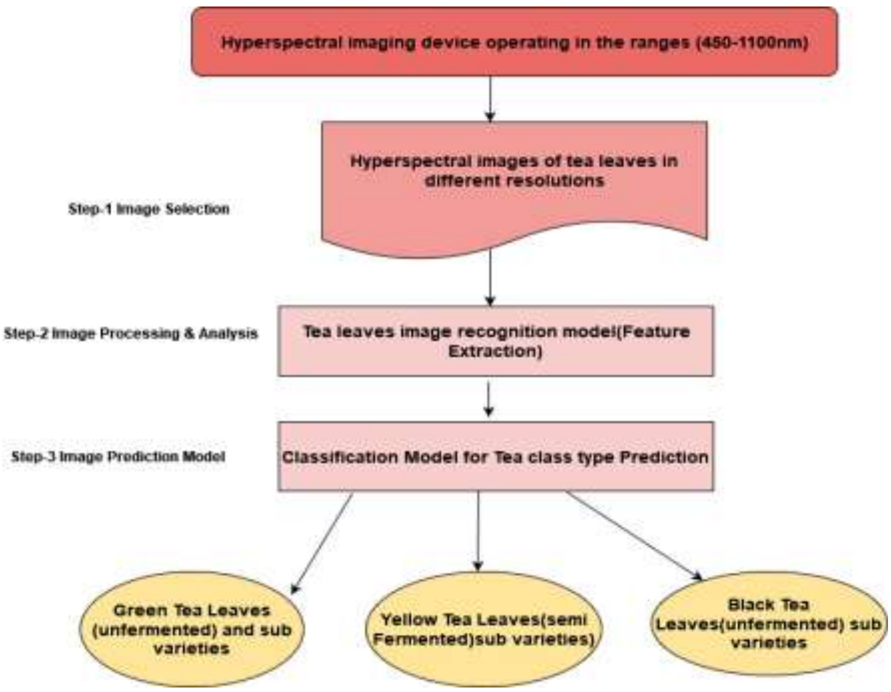

Figure 2. Level-2 of the proposed methodology for hyperspectral tea image recognition and tea type prediction

3.1. Tea leaf sample collection

The tea leaf dataset of 1 lakh samples have been collected from Kaggle, which were trained through proposed CNN model and classified with improved RFO ML technique. The tea leaves were taken using a 12 megapixel mobile camera in natural settings. Three types of tea-yellow, green, and black-that were bought from large supermarket stores and online were the samples utilized in the experiment. A few of them are yellow tea: Pingyang Huangtang (PYHT, made in Wenzhou, China), Mogan Huangya (MGHY, made in Huzhou, China), Mengding Huangya (MDHY, made in Ya'an, China), Huoshan Huangya (HSHY, made in Lu'an, China), and Junshan Yinzhen (JSYZ, made in Yueyang, China). Liuan Guapian (LAGP, made in Lu'an, China) and Maofeng (MF, made in Huangshan, China) are two examples of green tea. It is essential to gather the same category of tea from several manufacturers in order to gain additional samples.

For instance, Qimen County, Huangshan City, is the geographical birthplace of Qimen black tea. We continue to purchase black tea from various companies, such as Qihong Tea Limited Company, Huangshan, China (QMQH), Anchi Tea Limited Company, Chizhou, China (ACBT), Xiaolukou Tea Limited Company, Huangshan, China (XLBT), Gaoxiang Black Tea Factory, Huangshan, China (GXBT), and Qimen Tea Limited Company, Huangshan, China (HSBT). Additionally, Maofeng, or green tea, was gathered from various production companies, such as Yijiangyuan Tea Limited Company in Huangshan, China (YJYMF), Beijing Zhangyiyuan Jingtailong Tea Limited Company in Huangshan, China (ZYYMF), Ziwei Tea Limited Company in Huangshan, China (ZWMF), and Guangming Tea Limited Company in Huangshan, China (GMMF).

3.2. Noise reduction and image calibration

In hyper spectral imaging (HSI) data, the presence of noise can adversely affect machine learning applications, as highlighted in this research. Therefore, it is crucial to preprocess the HSI data using noise reduction techniques to improve the efficiency of tea class prediction, as depicted in (2) [22]. In the entire hyperspectral image acquisition system, the equipment used to capture the images can introduce noise reflectance, altering the distribution of emitted light reflectance across the surface of the material in the wavelength range covered by the spectral camera. It is essential to consider the emitted light source reflectance as constant across all the wavelengths within the given range [23]. Proper treatment of these factors ensures accurate and reliable analysis of the HSI data for tea classification purposes. For each spectral channel k, the hyperspectral camera output I in exposure time t is:

$$I\ (k, t) = L\ (k).\ C\ (k).t + DC\ (t) \tag{2}$$

The calibrated image reflectance is measured as:

$$HSI - R_{(x,y,k)} = \frac{SI-R_{(x,y,k)}-SI-D_{(x,y,k)}}{SI-W_{(x,y,k)}-SI-D_{(x,y,k)}} \tag{3}$$

HIS-R is the calibrated reflectance of the hyperspectral image acquired with respect to the spatial information ‘x’ and ‘y’ for the wavelength ‘k’ as shown in (3). Reflectance is calculated from the references and the light source distribution in various spectral bands [24]. Where the raw spectral capture is represented as SI-R with respect to x and y spatial information and k spectral information. The dark references image intensity is represented as $SI - D_{(x,y,k)}$ and the white reference is $SI - W_{(x,y,k)}$.
The identification of tea leaves is clearly mentioned for prediction of different tea types as shown in Figure 3. In RF method every time a specified number of random features are selected for considering the leaf detection process [25]. At each level based on the feature decision the tree grown predicts the target class. The process and stages of layers show the categorization of tea types in detail as shown in Figure 4. Corrected image collection is CI = {ci1, ci2, ci3 … cin}. Where: FC is fully connected and RF is random forest.

4. RESULTS AND DISCUSSION

The tea leaf samples were collected from the West Bengal province in the different estates such as Banarhat Tea Estate, Karballa Tea Estate, New Dooars Tea Estate, and Mim Tea Estate as shown in Table 2 [26]. The tea leaf samples were collected from the Assam province estates like Halmari Tea Estate [27], Mangalam Tea Estate [28], Corramore Tea Estate, Monabari Tea Estate [29].

In this paper a novel method is proposed to combine the different features of tea leaves extracted using electronic nose and tongue sensors, along with hyperspectral data obtained from spectral images acquired via a hyperspectral image system. The combined features undergo processing through CNN model for better filter identification. While there are multiple CNN architectures for image feature extraction, our study employs an optimal 12-layer CNN model, adept at autonomously learning distinctive tea leaf characteristics for categorizing them as green, yellow, or black.

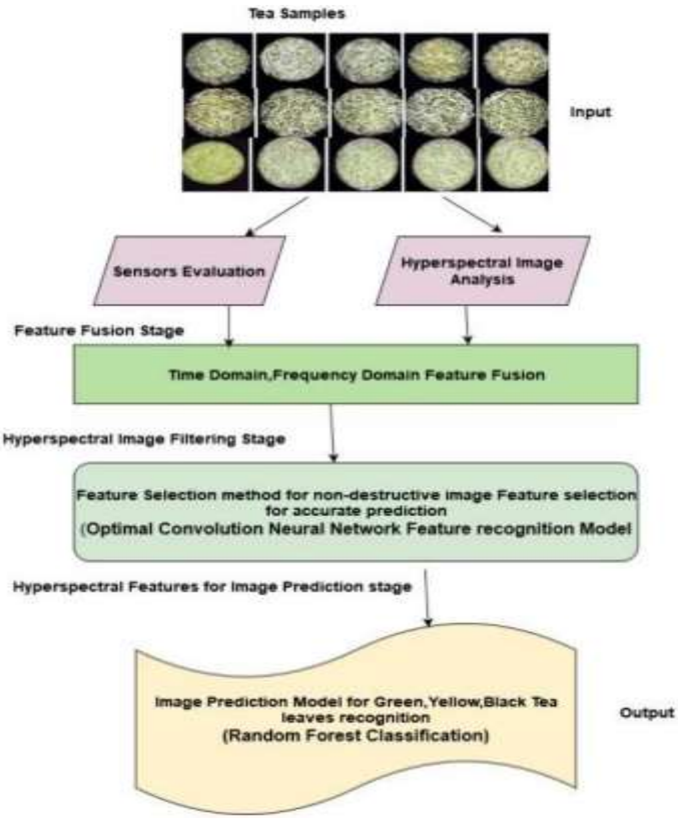

Figure 3. Proposed architecture tea leaves characteristics identification model for prediction of tea type (green, black, and yellow)

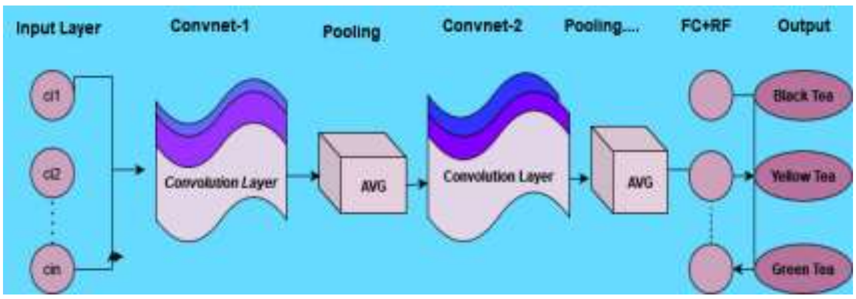

Figure 4. Calibrated hyperspectral image analysis using O-ConvNet-RF model

Table 2. Tea samples collection from production sources in India

State province	Estate samples collected	Number of samples
West Bengal	Banarhat Tea Estate	50
	Karballa Tea Estate	50
	New Dooars Tea Estate	50
	Mim Tea Estate	50
Assam	Halmari Tea Estate	50
	Mangalam Tea Estate	50
	Corramore Tea Estate	50
	Monabari Tea Estate	50

The novelty of this model is that the chemometrics and the image analysis features are combined for automatic tea leaf features identification. In a later stage, the RF method is used for the classification and prediction of the correct type of tea including sub-type based on the quality parameters. The tea polyphenols and amino acids present in the tea leaves decide the product type and benefits, so overall the suggested model has shown better accuracy than individual feature extraction analysis. The method followed in this paper is the combination of the two different approaches, which results in a better performance of the prediction as all the possible features are extracted in the fusion as shown in Table 3.

Table 3. Results of prediction for individual method and combination

Model	Green tea	Yellow tea	Black tea
Sensory evaluation (E-nose, E-tongue)	76% (194/256)	73% (186/256)	75% (192/256)
HIS+CNN	85% (217/256)	82% (209/256)	85% (217/256)
Sensory evaluation+HIS+CNN	89% (227/256)	88% (225/256)	90% (229/256)
Sensory evaluation+HIS+CNN+RF	95% (244/256)	96% (246/256)	96% (246/256)

To better understand the performance of our model in this approach confusion matrix as shown in Table 4, is used to evaluate the model against different measures of prediction. Optimized-convolutional neural network-random forest (O-ConvNet-RF) model is used to calculate different predicted values performance measures using the following evaluation measures as shown in Table 4.

Table 4. Evaluating optimized-convolutional neural network-RF model using confusion matrix

		Actual class	
	Confusion matrix	Positive	Negative
Predicted class	Positive	TP	FP
	Negative	FN	TN

$$precision = \frac{TP}{TP+FP} \quad (4)$$

$$recall = \frac{TP}{TP+FN} \quad (5)$$

$$F - Measure = \frac{2*Precision*recall}{precision+recall} \quad (6)$$

In (4), ‘TP’ means true positive i.e., the actual class and the predicted class are matching and ‘TN’ means the actual class and the predicted class are negative [30], ‘FP’ means the actual class is negative and the predicted class is positive whereas in (5), the ‘FN’ means the predicted class is negative and the actual class is positive and recall is calculated. In (6) shows the predicted values.

In Table 5, the various methods and its accuracy is given in detail and comparison with our proposed methodology is shown. The accuracy, FI score, recall and throughput values are observed to be improved. The presentation and illustration of the comparison of results are depicted in Figure 5, showcasing the performance of various methodologies. The methodology we propose exhibits a notably superior level of accuracy and throughput when compared to other methods currently in existence. Accuracy pertains to the degree of precision and correctness exhibited by the model's predictions, whereas throughput denotes the velocity and efficacy of processing and delivering outcomes. The findings unequivocally demonstrate that our methodology surpasses alternative approaches, yielding outcomes in tea classification tasks that are both more dependable and efficient. The aforementioned result highlights the superiority and efficacy of our suggested methodology in attaining precise and prompt outcomes, thereby guaranteeing its practical relevance and capacity to enhance the evaluation of tea quality.

Table 5. States-of-art comparison of results

Method	Accuracy (%)	Map (%)	F1 score (%)	Recall (%)	Throughput (%)
SVM	89.23	89	90.12	90.23	91.32
DT	90.25	90	89.45	91.27	92.54
X-boosting	91.24	92	91.32	90.28	93.21
GA	92.42	88	94.51	93.76	90.83
KNN	95.45	94	92.42	91.83	89.54
Proposed method	96.21	97	98.32	96.88	97.82

Figure 6 shows our method's training and validation accuracy. The training accuracy graph shows how well the model learns and adapts to the dataset. The model's ability to capture and learn from training data is shown in this Figure 6. Figure 7 shows how accurate our method is. This figure shows the model's test or validation dataset accuracy. It quantifies the model's accuracy in categorizing tea samples. These figures are crucial to evaluating our proposed methodology. Figure 6 shows the model's ability to learn and generalize from training data, while Figure 7 shows its real-world accuracy. These figures demonstrate that our method can accurately classify tea.

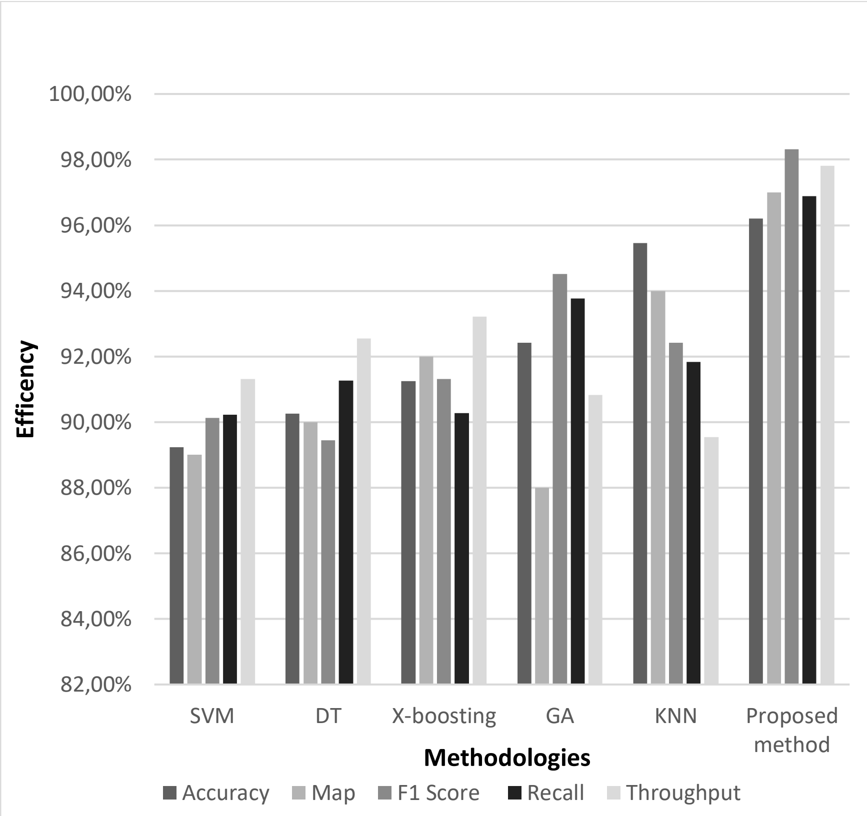

Figure 5. Comparison of techniques

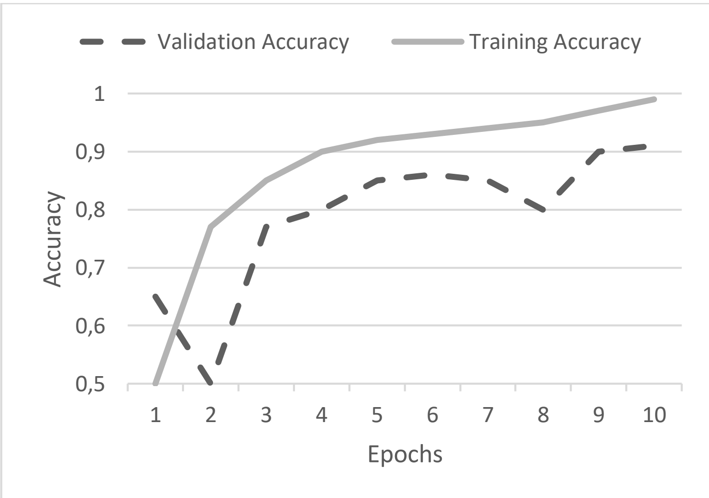

Figure 6. Training accuracy vs validation

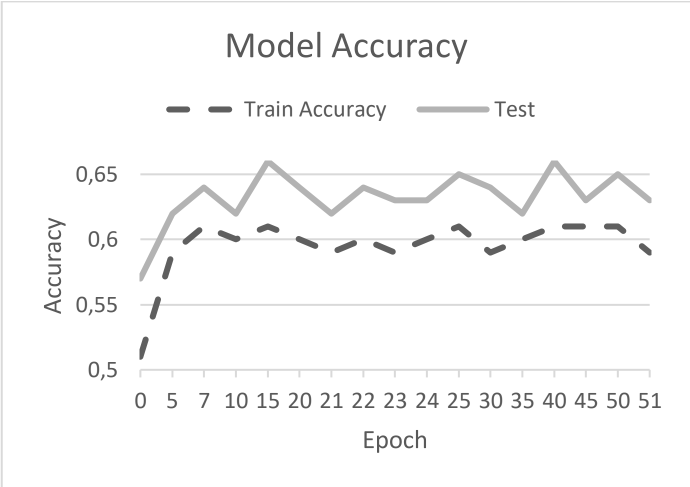

Figure 7. Train vs test accuracy

5. CONCLUSION

Several tea processing methods can be detrimental to tea quality due to their exposure to various environmental factors. In the proposed methodology, two distinct approaches were employed to attain the highest possible accuracy in the tea processing process. Although this method is non-destructive and may require more time, hyperspectral image recognition can significantly assist tea vendors in achieving better tea quality and increased profits. The results obtained from both the level-1 and level-2 approaches have shown outstanding performances. In comparison, the combined utilization of these two levels demonstrated superior accuracy in predicting tea classes when compared to a single approach.

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BIOGRAPHIES OF AUTHORS

Likitha Gongalla received her M. Tech Degree in CSE from Symbiosis Institute of Technology affiliated to JNTUH. Currently she is pursuing her Ph.D. Degree in School of Computer Science and Engineering, VIT-AP University, Andhra Pradesh, India, as internal full time research scholar. She worked as Assistant Professor in the Department of Computer Science and Engineering, MallaReddy College of Engineering and Technology, Maisammaguda, Telangana, India. Her research areas include computer vision, machine learning, deep learning, and artificial intelligence. She has more than 6 years of experience in teaching. She has published in two technical conferences and one technical research article. She published one patent on supply chain coordination in the internet of things for fresh agricultural products. She can be contacted at email: ankithareddy032@gmail.com.

Monali Bordoloi received B.E. degree in Computer Science and Engineering from the Gauhati University, Assam, India in 2013, M.Tech. degree in Computer Science and Engineering from the National Institute of Technology, Silchar, India in 2015, and the Ph.D. degree in Computer Science and Engineering from the National Institute of Technology, Silchar, in 2021. She is currently working as an Assistant Professor Senior Grade 1 in Vellore Institute of Technology–Andhra Pradesh University. She has 9 years of research experience in the field of artificial intelligence, machine learning, natural language processing, data mining, data analytics, information retrieval, and text classification. She has published 10 international journals, 4 international conference papers, and 3 book chapters. She has also been awarded the best paper award in two of her publications. She is the recipient of the Young Researcher Award 2020. She has also served as the organizing member of several workshops and research conclave organized by the National Institute of Technology, Silchar, India and VIT-AP university. She has reviewed manuscripts of IEEE transaction on artificial intelligence, expert systems with applications, and information sciences. She is also a reviewer and professional member of the Institute of Scholars (InSc). She can be contacted at email: monali.bordoloi@gmail.com.