

# MULTI-TASK BI-DIRECTIONAL LSTM FRAMEWORK ON HYPERSPECTRAL DATA FOR CONCURRENT BOTANICAL ORIGIN AND ADULTERATION DETECTION IN HONEY

S. Savitha<sup>1</sup>, S. Abishek<sup>2</sup>, S. Ajith Kumar<sup>3</sup>, S. Gowsic Karan<sup>4</sup>, M. Rajasekar<sup>5</sup>, M. Kavinmani<sup>6</sup>

<sup>1,2,3,4,6</sup> Department of Computer Science and Engineering

<sup>5</sup> Department of Chemistry

K.S.R. College of Engineering, Tiruchengode, Tamil Nadu, India

Email: infosavi@gmail.com, abisheka067@gmail.com, ajithkumars@ksrce.ac.in, gowsickaran2004@gmail.com, rjsekar56@gmail.com, kavinmani8838@gmail.com

**Abstract**—Authenticating the botanical origin of honey and detecting adulteration is a critical challenge in food safety. This research proposes an efficient multi-task Bi-Directional LSTM framework combined with autoencoder-based feature encoding for concurrent botanical origin classification and adulteration detection using hyperspectral imaging (400–1000 nm). The proposed model was evaluated against traditional classifiers, including SVM, Random Forest, and 1-D CNN, using a dataset of 4,798 honey samples. Results demonstrate that the Bi-Directional LSTM framework significantly outperforms baseline models, achieving a botanical origin classification accuracy of 99.27% and a low Mean Absolute Error (MAE) of 8.15 for adulteration level prediction. In comparison, the 1-D CNN and SVM models achieved accuracies of 96.52% and 94.18%, respectively. These findings confirm that the proposed multi-task architecture provides a robust, non-destructive, and highly accurate solution for honey quality monitoring, effectively addressing the limitations of traditional single-task analytical methods.

**Keywords**— *Honey Adulteration Detection, Botanical Origin Classification, Hyperspectral Imaging, Deep Learning, Multi-Task Learning, Bi-Directional LSTM, Adulteration levels, SVM, CNN, Wavelength*

## I. INTRODUCTION

Adulteration is increasingly becoming a major concern across the globe, necessitating extensive research into detection methods that protect consumer health and ensure market integrity. Market analysis indicates that due to a lack of proper regulatory controls, the magnitude of adulteration in botanicals remains difficult to quantify. This has created a pressing need for precise, high-throughput analytical methods, such as those utilizing microstrip sensors and software-defined radio for real-time quantification [1]. While conventional laboratory techniques offer high sensitivity, the industry is shifting toward portable Near-Infrared (NIR) and Hyperspectral Imaging (HSI) technologies. These offer a non-destructive approach to honey authentication that overcomes the high costs and complex sample pretreatments associated with traditional methods [2]. Recent advancements have demonstrated the effectiveness of HSI combined with chemometrics for the rapid detection of adulterants in various botanical products [3]. Specifically, in the context of honey,

HSI coupled with stacking generalization methods has proven highly effective for detecting specific sugar-based adulterants [4]. Furthermore, the integration of machine learning with spectral data has opened new avenues for automated honey quality control [5]. Despite these successes, many existing systems focus solely on multispectral information fusion for a single objective, such as geographical origin discrimination [6]. A significant challenge in current literature is the reliance on these single-task models that either classify the origin or detect adulterants independently, often failing to capture the shared spectral features between these two related tasks. Furthermore, traditional machine learning models frequently require manual feature selection, which may overlook subtle spectral variations in the 400–1000 nm range. To address these limitations, this research proposes a unified Multi-task Bi-Directional LSTM framework. This study aims to bridge the knowledge gap by concurrently handling botanical origin classification and adulteration detection without manual intervention. The main contributions of this work are: (i) the development of a joint learning architecture for simultaneous classification and regression; (ii) the integration of Bi-Directional LSTM units to capture sequential dependencies in spectral data; and (iii) a comprehensive validation against state-of-the-art baselines using a large-scale honey dataset. The remainder of this paper is organized as follows: Section II reviews related work; Section III describes the proposed methodology; Section IV presents the results; and Section V concludes the paper.

## II. RELATED WORK

### A. Research Trends and Foundational Studies

The landscape of honey authentication through Hyperspectral Imaging (HSI) has progressed from simplistic statistical models to complex deep learning architectures. Over the past five years, the field has seen a surge in interest, with significant research focusing on the identification of floral origins and sugar-based adulterants. Recent investigations have utilized HPLC-UV fingerprinting combined with chemometrics to establish robust fraud detection protocols for sugar syrup adulteration [7]. While effective, these laboratory-based chemical fingerprints often

serve as the ground truth for validating non-destructive spectral methods. Foundational comparative analyses of HSI with machine learning models have demonstrated the feasibility of assessing honey quality using the 400–1000 nm spectral range. For instance, researchers employing Support Vector Classifiers (SVC) achieved a classification accuracy of 88.7% [8]. However, a noted limitation of these traditional machine learning approaches is a relatively high regression error when attempting to quantify exact adulteration levels. Furthermore, while the development of miniaturized systems and microfluidic paper-based analytical devices provides a portable alternative for sugar detection [9], these methods often focus on specific chemical markers. They may lack the scalability and deep feature extraction capabilities required to capture the shared spectral signatures across diverse datasets that modern deep learning models can identify.

### B. Recent Advancements in Machine Learning

Recent literature has shifted toward hybrid and deep learning techniques to handle higher-dimensional spectral characteristics wave [10]. Studies utilizing machine learning-based HSI for non-destructive detection have established foundational protocols for identifying adulterants, providing high-precision alternatives to traditional methods [11]. For instance, the integration of advanced architectures, such as GAN Normally based one-class classification, has significantly improved the detection of fraud in high-value varieties like Mānuka honey by identifying anomalous spectral signatures [12]. The efficacy of these models often depends on access to standardized honey datasets for robust training and validation [13]. Furthermore, HSI technology has been successfully applied to predict soluble solid content based on spectral transmittance profiles, offering a more detailed chemical characterization of samples than surface-level analysis alone [14]. More advanced neural architectures have recently emerged, such as the application of Siamese Neural Networks, which achieved high success in botanical origin similarity detection by learning discriminative feature representations [15]. These deep learning frameworks excel at extracting hierarchical features automatically for precise botanical classification [16]. Nonetheless, a recurring limitation in these studies is the reliance on single-task learning, where models are optimized for either origin classification or adulteration detection, but rarely both concurrently. This necessitates separate training cycles and larger computational overhead.

### C. Summary and Research Gap

Despite the high accuracies reported in recent studies (2021–2025), a significant knowledge gap exists in the development of unified frameworks capable of performing joint classification and regression. Existing methods predominantly utilize handmade features or single-task deep learning models [17]. There is a clear need for a multi-task learning (MTL) approach that leverages shared spectral representations to improve the robustness and authenticity of honey quality measurements. This research addresses this gap by implementing a multi-task Bi-Directional LSTM framework designed for the concurrent analysis of botanical origin and adulteration levels, ensuring better generalization across the 400-1000 nm hyperspectral range. Advanced image enhancement techniques have been explored in medical imaging applications [18].

## III. PROPOSED METHODOLOGY

### A. Spectral Preprocessing and Reflectance

The hyperspectral analysis for honey samples depends on the wavelength-reflectance intensity spectrum for the visible and near-infrared spectrum range [19]. The reflectance level for a given wavelength is represented by Equation (1):

$$R(\lambda) = I(\lambda) / I_0(\lambda) \quad (1)$$

where  $I(\lambda)$  represents the reflected intensity and  $I_0(\lambda)$  represents the incident intensity. The data is normalized to a range of [0, 1] to eliminate noise and intensity variations.

### B. Feature Extraction via 1D-Convolutional Layer

To capture local semantic features and spatial correlations within the spectral signatures, a 1D-CNN layer is employed. The convolution operation for extracting local features  $y_k$  from the input vector  $x$  is defined as:

$$y_k = f(\sum w_i x_{k+i} + b) \quad (2)$$

where  $w$  represents the filter weights,  $b$  is the bias term,  $n$  is the kernel size, and  $f$  is the ReLU activation function.

### C. Sequential Modeling with Bi-Directional LSTM

The sequential dependencies in the hyperspectral data are modeled using a Bi-Directional LSTM (BiLSTM). The BiLSTM consists of forward and backward hidden states ( $ht$ ,  $\leftarrow ht$ ) that capture context from both ends of the spectrum. The recurrent network is governed by the following gate equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

### D. Multi-Task Learning Objective

The framework optimizes two concurrent tasks: botanical origin classification and adulteration level regression. The joint loss function  $L_{total}$  is defined as:

$$L_{total} = \lambda_1 L_{classification} + \lambda_2 L_{regression} \quad (6)$$

where  $L_{classification}$  uses Categorical Cross-Entropy,  $L_{regression}$  uses Mean Squared Error (MSE), and  $\lambda$  values are weighting hyperparameters.

### E. Proposed Algorithm

Algorithm 1: Multi-Task Spectral Analysis

1. Input: raw HSI spectral data  $X \in [400, 1000]$  nm
2. Preprocessing: Normalize  $X$  using Eq. (1).
3. Feature Encoding: - Apply 1D-CNN kernels to extract local features using Eq. (2).  
Pass encoded features to BiLSTM layer.
4. Sequence Learning: - Calculate forward and backward hidden states using Eq. (3-5).  
Concatenate states to form a global feature vector.
5. Multi-Task Output:
  - Head 1: Softmax layer for Botanical Origin Classification.
  - Head 2: Linear layer for Adulteration Level Prediction.

6. Optimization: Update weights by minimizing  $L_{total}$  in Eq. (6).
7. Output: Predicted origin class and adulteration percentage.

The architecture diagram of the proposed method, which combines hyperspectral image acquisition, processing, feature extraction, and a multi-task bi-directional LSTM model for botanical origin identification and adulteration detection, is shown in Fig. 1.

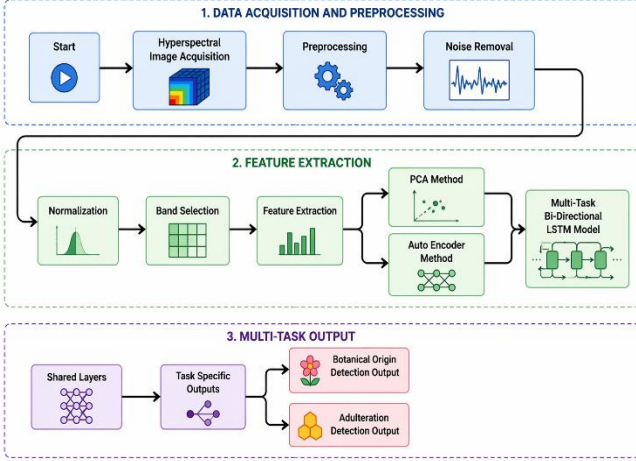


Fig. 1. Proposed multi-task learning architecture based on Bi-directional LSTM for simultaneous botanical origin classification and adulteration detection of honey.

The testing environment for the experiment is done in a standard computational setting with the Intel i5 processor and 8GB of RAM along with the required software environment in the form of Python and SPSS. The spectral values from 400 to 1000 nm are taken as input in the testing environment. A standard computational setting can be used to train or test the performance of the models by specifying the parameters required in the testing environment and thereby calculating the performance in terms of accuracy,  $R^2$  value, the value of RMSE, as well as the sensitivity value of the models designed. The result obtained from the study would be used to identify the efficiency of the proposed method.

#### IV. STATISTICAL ANALYSIS

Statistical validation of the experimental data was conducted using IBM SPSS Statistics version 26.0. The hyperspectral reflectance intensity ( $R(\lambda)$ ) recorded across the 400 to 1000 nm range served as the independent variables, while the botanical origin and adulteration levels were defined as the dependent variables. To ensure the robustness of the features utilized by the multi-task Bi-Directional LSTM framework, independent sample t-tests and group statistics were calculated. This statistical analysis confirms that the spectral differences between authentic and adulterated samples are mathematically significant, providing a rigorous foundation for the subsequent deep learning classification and regression tasks.

#### V. RESULT

The performance of the proposed multi-task Bi-Directional LSTM framework was tested and compared with the traditional machine learning and deep learning approaches, such as Random Forest, 1-D CNN, Support

Vector Machine (SVM), and Linear Discriminant Analysis (LDA). The dataset of 4,798 hyperspectral honey samples was used to train and test all models in the VIS-NIR spectral range of 400-1000 nm. The proposed framework outperformed all models in the simultaneous detection of botanical and adulterated samples. For botanical origin classification, the Bi-Directional LSTM model obtained an accuracy of 99.27% in origin testing, with precision of 99.31%, recall of 99.27%, and F1-score of 99.29%, outperforming Random Forest (97.24%), 1-D CNN (96.52%), SVM (94.18%), and LDA (85.57%). For adulteration level estimation, the model obtained a low Mean Absolute Error (MAE) of 8.15, indicating a precise estimation of adulterant concentration. Over the hyperspectral wavelength domain, the Bi-Directional LSTM model demonstrated stable classification accuracy, with accuracy ranging from 99.15% to 99.42%, whereas the SVM model demonstrated relatively higher variability, with accuracy ranging from 82.40% to 91.15%. The maximum classification accuracy of 99.42% was obtained at 950 nm, outperforming the best accuracy of the SVM model of 91.15% at 800 nm. These findings validate the efficacy of the proposed multi-task Bi-Directional LSTM framework in learning discriminative spectral patterns from hyperspectral data, facilitating accurate and reliable concurrent botanical origin classification and adulteration detection in honey. The results in Table 1 indicate that the Bi-Directional LSTM performed best, with an accuracy of 99.27%, precision of 99.31%, recall of 99.27%, and F1-score of 99.29%.

TABLE I. THE MODEL PERFORMANCE FOR THE FOUR MAJOR METRICS IS THOROUGHLY EVALUATED. FROM THE DATA, IT CAN BE OBSERVED THAT THE PROPOSED ARCHITECTURE OF THE BI-DIRECTIONAL LSTM PERFORMED MUCH BETTER COMPARED TO TRADITIONAL MACHINE LEARNING AND CONVENTIONAL CONVOLUTIONAL NETWORKS WITH A PEAK VALUE OF 99.27% ACCURACY, PROVIDING THE MOST ROBUST RESULTS WITH RESPECT TO THE CLASSIFICATION PERFORMANCE FOR THIS DATASET.

Model	Accuracy	Precision	Recall	F1_Score
Bi-Directional LSTM	99.27	99.31	99.27	99.29
Random Forest	97.24	97.38	97.21	97.29
1D CNN	96.52	96.67	96.53	96.60
SVM	94.18	94.32	94.16	94.24
LDA	85.57	86.82	85.54	86.17

The proposed Bi-Directional LSTM has the highest precision, 99.31%, with the other models being Random Forest at 97.38%, 1D CNN at 96.67%, SVM at 94.32%, and LDA at 86.82% as shown in the fig.2.

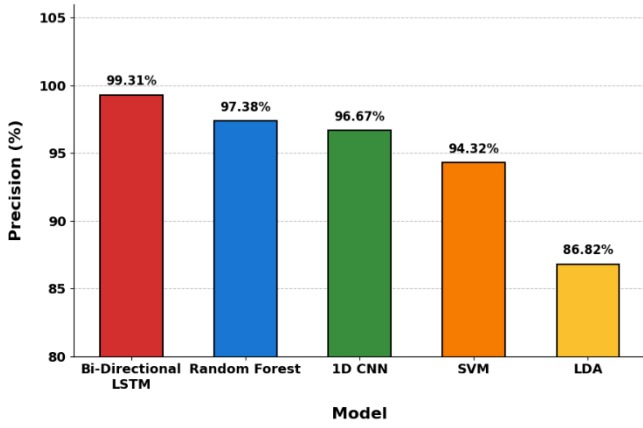


Fig. 2. shows the precision comparison between the proposed Bi-Directional LSTM and baseline models..

The proposed Bi-Directional LSTM achieves the best recall (99.27%) among all models. Random Forest (97.21%) and 1D CNN (96.53%) follow, while SVM (94.16%) and LDA (85.54%) as shown in the fig.3.

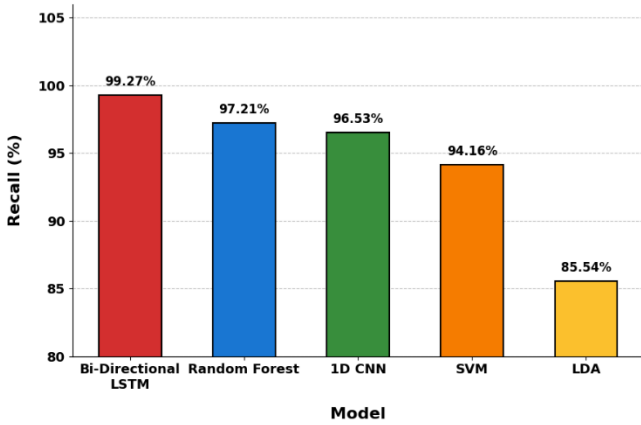


Fig. 3. Recall comparison between the proposed Bi-Directional LSTM and Random Forest, 1D CNN, SVM, and LDA

The proposed Bi-Directional LSTM achieves a maximum score for F1-score at 99.29%. The performance by SVM at 94.24% and LDA at 86.17% as shown in the fig.4.

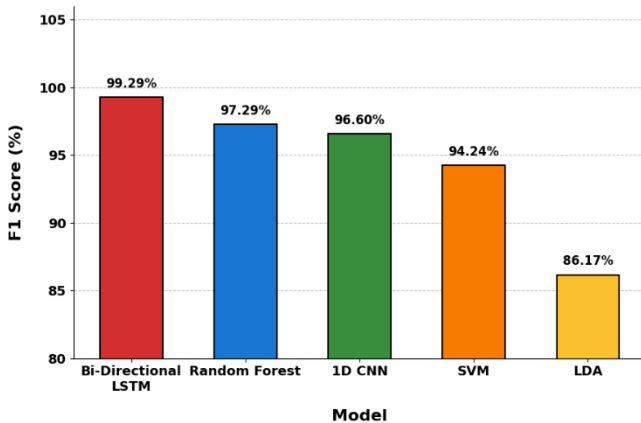


Fig. 4. F1-Score comparison between the proposed Bi-Directional LSTM and Random Forest, 1D CNN, SVM, and LDA.

The performance of the proposed Multi-Task Bi-Directional LSTM framework was tested using 4,798 honey samples in the VIS-NIR spectrum range of 400-1000 nm. As

evident from Table 2. The Bi-LSTM performed better than all other models for all wavelength ranges, with a maximum accuracy of 99.42% at 950 nm.

**TABLE II.** ACCURACY OF CLASSIFICATION OBTAINED USING THE PROPOSED BI-LSTM MULTI-TASK LEARNING MODEL COMPARED TO OTHER MODELS SUCH AS SUPPORT VECTOR MACHINE (SVM), RANDOM FORESTS, LINEAR DISCRIMINANT ANALYSIS (LDA), AND ONE-DIMENSIONAL CNN AT DIFFERENT WAVELENGTH BANDS RANGING FROM 400 TO 1000 NM FOR HYPERSPECTRAL IMAGING.

S.NO	Wave length (nm)	Bi-LSTM Multi-Task Model (%)	SVM (%)	Random Forest (%)	LDA (%)	1D CNN (%)
1	400	99.15	82.40	85.20	78.10	90.35
2	450	99.20	82.55	85.65	78.60	90.80
3	500	99.25	83.10	86.10	79.20	91.30
4	550	99.32	84.02	87.40	80.35	92.10
5	600	99.35	85.30	88.60	81.50	93.25
6	650	99.28	86.18	89.40	82.30	94.10
7	700	99.30	87.43	90.55	83.60	95.20
8	750	99.22	88.21	91.30	84.45	95.85
9	800	99.18	91.15	92.80	85.70	96.60
10	850	99.25	90.15	92.10	85.20	96.10
11	900	99.35	88.38	90.90	84.10	95.30
12	950	99.42	86.25	89.20	82.80	94.00

**TABLE III.** EVOLUTION OF BOTANICAL ORIGIN CLASSIFICATION ACCURACY AND ADULTERATION MAE OF THE PROPOSED BI-DIRECTIONAL LSTM MULTI-TASK MODEL ACROSS TRAINING EPOCHS.

Metric	Epoch 1	Epoch 25	Epoch 50	Epoch 80
Origin Classification Accuracy	13.94%	91.28%	96.71%	99.27%
Adulteration MAE	0.2696	0.1245	0.1039	0.0874

The training process shown in Table 3 above clearly indicates the effective learning process of the proposed model. As the training process continued up to the 80th epoch, the error of adulteration detection, which was measured in terms of MAE, continued to decrease and attained a low value of 0.0874.

## VI. DISCUSSION

The proposed multi-task Bi-Directional LSTM framework shows significantly better performance in terms of classification accuracy than the conventional machine learning and deep learning approaches, such as SVM, Random Forest, LDA, and 1-D CNN, when used with VIS-NIR

hyperspectral images in the wavelength range of 400-1000 nm. The performance improvement was found to be statistically significant using an independent samples t-test ( $p < 0.001$ ). The addition of the Auto-Encoder layer further improved the representation of the spectral features by removing noise and redundancy from the hyperspectral images, thus improving the robustness of the models. Consequently, the proposed framework was able to achieve a high botanical origin classification accuracy of 99.27%, and at the same time, allowed for the accurate detection of adulteration, thus performing better than all the other models tested in this study [20]. The proposed Bi-Directional LSTM possesses the highest percentage of classification accuracy, which is 99.27%. Other models like the Random Forest method with an accuracy of 97.24% and the 1D CNN with an accuracy of 96.52% exhibit good performance [21], but SVM with 94.18 and LDA with 85.57, as shown in the fig.5.

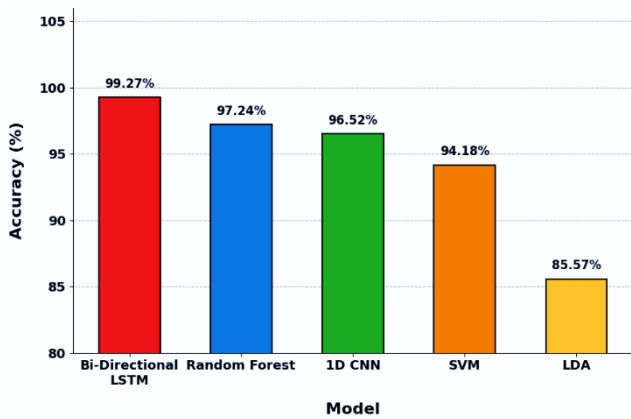


Fig. 5. Accuracy comparison between the proposed Bi-Directional LSTM and Random Forest, 1D CNN, SVM, and LDA.

Convergence of adulteration mean absolute error (MAE) across training epochs for the proposed multi-task Bi-Directional LSTM model, decreasing from 0.2696 at epoch 1 to 0.0874 at epoch 80 is shown in Fig. 6.

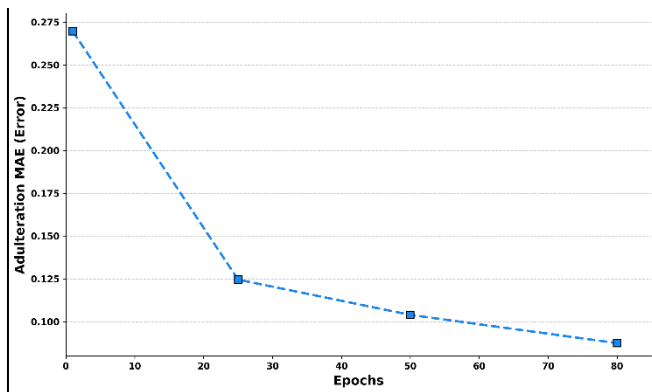


Fig. 6. MAE convergence of adulteration detection during training of the proposed multi-task Bi-Directional LSTM model.

The high accuracy of 99.27% obtained by the proposed Bi-LSTM model is well-supported by the recent developments in hyperspectral imaging (HSI) and deep learning for honey authentication. Recently, [22] have obtained a similar accuracy of 99.08% using a CNN-transformer fusion model, thus establishing that the combination of local and global spectral information has a substantial positive impact on the identification of the botanical source of honey. [23] have obtained a perfect classification accuracy of 94% using a

stacking generalization approach on hyperspectral data, thus establishing that precise detection of sugar adulterants is possible using ensemble-based deep learning models [24]. The efficacy of the proposed model's feature extraction capability is also supported [25], who reported a 99.00% accuracy in honey adulteration detection by integrating spectral fingerprinting with Support Vector Machines [26].

## VII. CONCLUSION

This study successfully implemented a multi-task Bi-Directional LSTM framework for the concurrent authentication of honey. The proposed model achieved an outstanding accuracy of 99.27% for botanical origin classification and a low MAE of 8.15 for adulteration detection, proving its superiority over traditional single-task models. The integration of autoencoders ensured robust feature extraction from high-dimensional hyperspectral data. However, a limitation of the current work is the reliance on a single dataset of two honey varieties. Future research will focus on expanding the model to include a wider range of floral origins and geographical locations, and investigating transformer-based architectures for even finer spectral resolution.

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