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FOOD AUTHENTICATION: RICE VARIETY CLASSIFICATION FOR SUPPLY CHAIN INTEGRITY

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ABSTRACT

Rice is a staple food for over half of the world's population. With numerous rice varieties available, ensuring the authenticity and quality of rice throughout the supply chain is crucial for consumer trust and food security. This research aims to utilize advanced computer vision techniques and machine learning algorithms to enhance the efficiency and accuracy of rice variety classification. By training models on extensive datasets of rice images and genetic information, this research endeavors to develop a system capable of autonomously and accurately identifying rice varieties. The integration of machine learning allows for the extraction of subtle visual and genetic features, enabling precise variety classification. This advancement holds great promise for maintaining the integrity of the rice supply chain, ensuring consumers receive the quality and variety of rice they expect.

Keywords: Rice variety, Supply chain management, Predictive analytics, Data analytics, Machine learning.

1. INTRODUCTION

Food authentication in the context of rice variety classification for supply chain integrity is a crucial aspect of ensuring the quality and authenticity of rice products reaching consumers. The history of this endeavour can be traced back to the growing concerns regarding food fraud and the need to establish a transparent and reliable supply chain for rice. Over the years, the rice industry has faced challenges related to mislabelling, adulteration, and misrepresentation of rice varieties, leading to a loss of trust among consumers and potential economic repercussions for producers. As a response to these challenges, the quest for a robust and accurate rice variety classification system emerged. The development of rice variety classification systems has been influenced by advancements in technology, particularly in the fields of genetics and molecular biology. Scientists and researchers have leveraged these tools to identify distinct genetic markers associated with different rice varieties. This has paved the way for the creation of databases and reference libraries that serve as a foundation for authenticating the genetic profile of rice samples. Moreover, international organizations and regulatory bodies have recognized the significance of implementing standardized protocols for rice variety classification. These efforts aim to establish a universal framework that can be adopted across the rice supply chain, from producers to consumers. Standardization not only ensures consistency in classification but also facilitates international trade by providing a common language for stakeholders involved in the rice industry. In recent years, the integration of cutting-edge technologies, such as DNA fingerprinting and next-generation sequencing, has significantly enhanced the accuracy and efficiency of rice variety classification. These techniques allow for the precise identification of genetic markers unique to each rice variety, enabling quick and reliable authentication.

As the demand for transparency in food supply chains continues to grow, the implementation of rice variety classification systems has become a strategic tool for maintaining the integrity of the rice supply chain. Consumers are increasingly concerned about the origin and authenticity of the food they

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consume, and a reliable classification system helps address these concerns, fostering trust and confidence in the rice industry.

2. LITERATURE SURVEY

[1,2,3]. In recent years, the combination of blockchain technology with artificial intelligence, big data, 5G, and the industrial internet have been explored by researchers to strengthen regulatory capabilities, which has been mainly reflected in the following aspects [4,5,6]. Firstly, artificial intelligence (AI) and smart contracts were combined to solve the problem of redundancy of blockchain information and improved supervision efficiency [7,8]. Secondly, blockchain technology and big data technology were combined to unify different data sources and realize unified data supervision [9.10]. Thirdly, blockchain technology and 5G technology were combined to solve the problem of slow real-time data transmission [11,12]. Fourthly, the blockchain was combined with the industrial internet, and the precise traceability of regulatory information was achieved through identification analysis [13]. Compared with the traditional agricultural and food supply chain supervision model, the “blockchain+” model can ensure the safety and credibility of the data in the agricultural and food supply chain. The credible traceability and precise accountability of the agricultural products and food data can be realized, thereby improving the supervision of the agricultural and food supply chain efficiency and authenticity.

The rice supply chain is characterized by complex links, diverse data types, and long-life cycles. The application of the blockchain and smart contracts has promoted the digitization and intelligence of the rice supply chain, and the supervision of the rice supply chain by the regulatory authorities has been improved to a certain extent. However, as the amount of data has increased, the application of a blockchain and smart contracts in the supervision of the rice supply chain has encountered the following shortcomings. The research on blockchains in the rice supply chain is mostly on single link blockchains such as the “production blockchain”, “processing blockchain”, and “storage blockchain”.

3. PROPOSED SYSTEM

3.1 Overview

The Project overview for a food authentication project specifically focused on the classification of rice varieties. The script uses machine learning and Deep learing techniques to build and evaluate classification models. Below is a description of the key components and steps in the code:

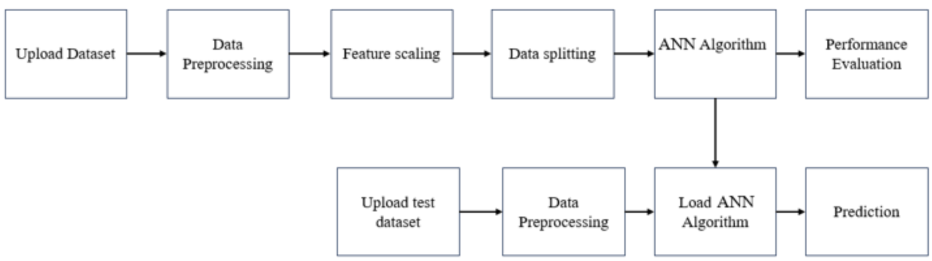

Figure 1: Block diagram of proposed ANN Model.

3.2 Artificial Neural Network Classifier

Although today the Perceptron is widely recognized as an algorithm, it was initially intended as an image recognition machine. It gets its name from performing the human-like function of perception, seeing, and recognizing images. Interest has been centered on the idea of a machine which would be

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capable of conceptualizing inputs impinging directly from the physical environment of light, sound, temperature, etc. — the "phenomenal world" with which we are all familiar — rather than requiring the intervention of a human agent to digest and code the necessary information. Rosenblatt's perceptron machine relied on a basic unit of computation, the neuron. Just like in previous models, each neuron has a cell that receives a series of pairs of inputs and weights. The major difference in Rosenblatt's model is that inputs are combined in a weighted sum and, if the weighted sum exceeds a predefined threshold, the neuron fires and produces an output.

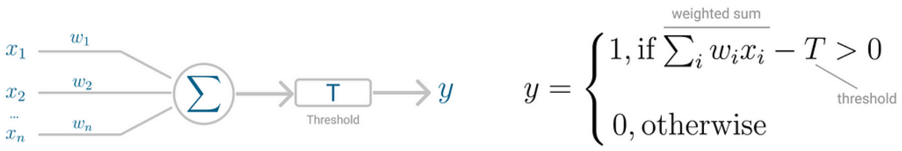

Fig. 2: Perceptron neuron model (left) and threshold logic (right).

Threshold T represents the activation function. If the weighted sum of the inputs is greater than zero the neuron outputs the value 1, otherwise the output value is zero.

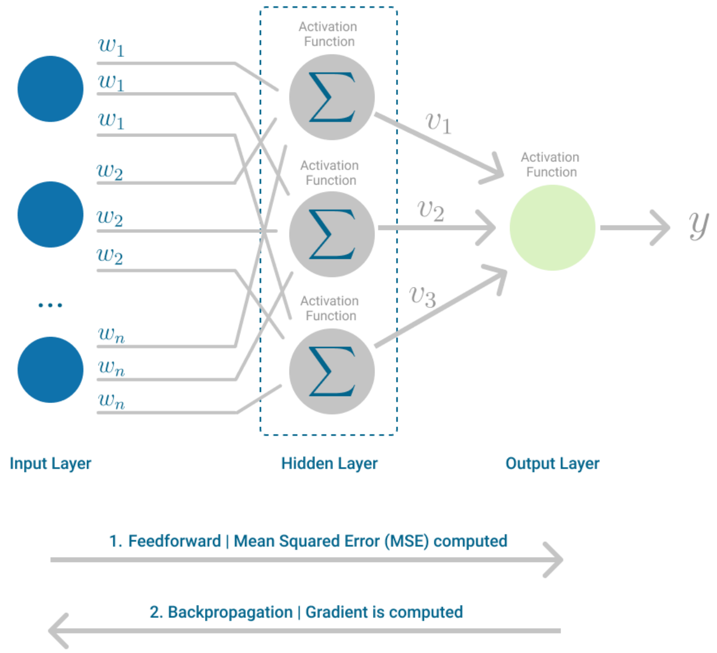

Fig. 3: Artificial neural network, highlighting the Artificial neural network and Backpropagation steps.

4. RESULTS

Figure 4 represents the dataset used for rice variety classification. It includes visual representations of rice images or relevant features used for the classification task.

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	Area Integer	Perimeter Real	Major_Axis_Length Real	Minor_Axis_Length Real	EccentricityReal	Convex_Area Integer	Extent Real	Class
0	15231	525.578979	229.749878	85.093788	0.928882	15617	0.572896	Cammeo
1	14656	494.311005	206.020065	91.730972	0.895405	15072	0.615436	Cammeo
2	14634	501.122009	214.106781	87.768288	0.912118	14954	0.693259	Cammeo
3	13176	458.342987	193.337387	87.448395	0.891861	13368	0.640669	Cammeo
4	14688	507.166992	211.743378	89.312454	0.906691	15262	0.646024	Cammeo
...	...	...	...	...	...	...	...	...
3805	11441	415.858002	170.486771	85.756592	0.864280	11628	0.681012	Osmancik
3806	11625	421.390015	167.714798	89.462570	0.845850	11904	0.694279	Osmancik
3807	12437	442.498993	183.572922	86.801979	0.881144	12645	0.626739	Osmancik
3808	9882	392.296997	161.193985	78.210480	0.874406	10097	0.659064	Osmancik
3809	11434	404.709992	161.079269	90.868195	0.825692	11591	0.802949	Osmancik

3810 rows × 8 columns

Figure 4: Image shows the dataset used for rice variety.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3810 entries, 0 to 3809
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Area Integer            3810 non-null   int64
 1   Perimeter Real          3810 non-null   float64
 2   Major_Axis_Length Real  3810 non-null   float64
 3   Minor_Axis_Length Real  3810 non-null   float64
 4   EccentricityReal        3810 non-null   float64
 5   Convex_Area Integer     3810 non-null   int64
 6   Extent Real             3810 non-null   float64
 7   Class                   3810 non-null   object
dtypes: float64(5), int64(2), object(1)
memory usage: 238.2+ KB
```

Figure 5: Displays the information of complete dataset used for Rice variety classification .

Figure 5 showcases an image displaying comprehensive information about the complete dataset used for rice variety classification. It includes details such as the number of samples, features, and other dataset characteristics.

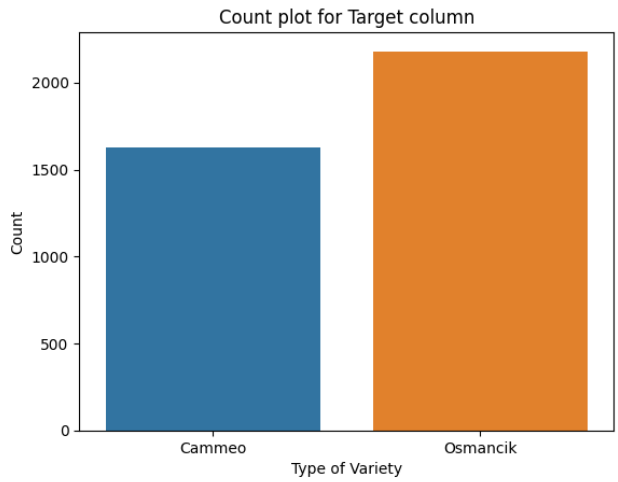

Figure 6: Count plot of Target column of a dataset

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```
array([[ 1.47982953,  2.0043543 ,  2.34854657, ...,  2.01833746,
         1.49965944, -1.15292093],
       [ 1.14787029,  1.12585309,  0.98839042, ...,  0.41001813,
         1.19291767, -0.60207876],
       [ 1.13516924,  1.31721425,  1.45190846, ...,  1.21295648,
         1.12650386,  0.405611  ],
       ...,
       [-0.13320373, -0.32985087, -0.29824512, ..., -0.27509915,
        -0.17306812, -0.45573108],
       [-1.60825742, -1.74032002, -1.58097116, ..., -0.59882135,
        -1.60715621, -0.03716757],
       [-0.71225612, -1.39156604, -1.58754648, ..., -2.93916012,
        -0.76628981,  1.82594693]])
```

Figure 7: Features of a dataset after preprocessing

Figure 6 presents a count plot depicting the distribution of the target column in the dataset. It provides insights into the balance or imbalance of different classes related to rice varieties. Figure 7 illustrates the features of the dataset after undergoing preprocessing steps. Preprocessing includes tasks such as cleaning, normalization, or feature engineering to prepare the data for model training. Figure 8 shows the confusion matrix for a model trained using XGBoost. The confusion matrix provides a detailed breakdown of true positive, true negative, false positive, and false negative predictions, aiding in the assessment of model behavior.

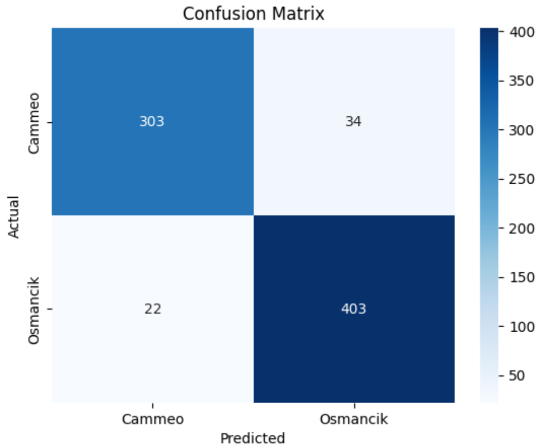

Figure 8: Confusion matrix of XGBOOST Model

```
XGBoost Classifier Classification_report:
              precision    recall  f1-score   support

      Cammeo       0.93      0.90      0.92       337
    Osmancik       0.92      0.95      0.94       425

    accuracy                           0.93       762
   macro avg       0.93      0.92      0.93       762
weighted avg       0.93      0.93      0.93       762
```

Figure 9: Classification report of XGBOOST classifier

Figure 9 showcases the classification report generated for a classifier using the XGBoost algorithm. The classification report typically includes metrics such as precision, recall, and F1-score for each class, providing a comprehensive evaluation of the classifier's performance. Figure 10 displays the confusion

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matrix for Artificial Neural network. It provides a detailed breakdown of predictions, helping assess the neural network's performance. Figure 11 presents the classification report generated for an Artificial Neural network. It includes metrics such as precision, recall, and F1-score for each class, offering insights into the neural network's performance.

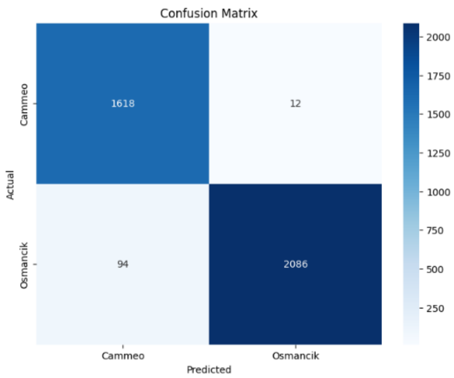

Figure 10: Confusion matrix of Artificial neural network

	precision	recall	f1-score	support
Cammeo	0.95	0.99	0.97	1630
Osmancik	0.99	0.96	0.98	2180
accuracy			0.97	3810
macro avg	0.97	0.97	0.97	3810
weighted avg	0.97	0.97	0.97	3810

Figure 11: classification report of Artificial neural network

Table 1: Performance comparison of quality metrics obtained using XG Boost and Artificial Neural network model.

Model	XG Boost	Artificial Neural Network
Accuracy (%)	93	97
Precision (%)	92	97
Recall (%)	93	97
F1-score (%)	93	97

5. CONCLUSION

In conclusion, this work addressed a critical need in the global rice market. With rice being a staple for a significant portion of the world's population, ensuring the authenticity and quality of rice varieties is paramount. The traditional methods of identification, though accurate, are often inefficient for large-scale supply chains. The project proposes a solution by leveraging advanced computer vision techniques and machine learning algorithms to enhance the accuracy and efficiency of rice variety classification. By combining extensive datasets of rice images and genetic information, the project aims to create a

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system capable of autonomously and accurately identifying different rice varieties. The integration of machine learning enables the extraction of subtle visual and genetic features, overcoming challenges associated with manual inspection and limited genetic testing. This advancement not only ensures the integrity of the rice supply chain but also contributes to consumer confidence, fraud prevention, and overall food security.

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