UNIVERSITI PUTRA MALAYSIA

ARTIFICIAL INTELLIGENCE SYSTEM FOR PINEAPPLE VARIETY CLASSIFICATION AND ITS QUALITY EVALUATION DURING STORAGE USING INFRARED THERMAL IMAGING

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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July 2022

Chair : Associate Professor Ir. Norhashila Hashim, PhD
Faculty : Engineering

Pineapple is a tropical fruit that is highly relished for its unique aroma and sweet taste. Monitoring of pineapple quality is essential in order to regulate proper postharvest handling and yield production. In the present study, infrared thermal imaging was used to determine the variety classification and quality attributes of pineapples, specifically total soluble solids (TSS), moisture content, pH, colour changes, and firmness based on various storage conditions (storage temperatures and storage days). Three pineapple varieties were used in this study which are MD2, Morris, and Josapine. A total of 1080 fresh pineapples at a ripening stage of Index 2 were used in this study. The samples were stored at three different storage temperatures i.e. in a cold storage room (5 °C), a controlled refrigerator (10 °C), and an air-ventilated laboratory room (25 °C) with a temperature range of ±2 °C and relative humidity of 85 to 90 %. For each variety, 30 samples were randomly selected for data collection at every seven days intervals (Day 0, Day 7, Day 14, and Day 21). Thermal images of pineapples were acquired at three different varieties at various storage conditions. By using first-order kinetics, the R^2 values of quality changes of pineapples ranged from 0.893 to 0.992. The results also demonstrated that the samples stored at 10 °C had the longest shelf life in relation to the changes in firmness and moisture content of the fruit. Principal component analysis was used to develop quantitative prediction models and clustering ability of three different varieties of pineapples. The optimal relations among all the image parameters successfully explained the robustness of the partial least squares (PLS) models which demonstrated a good prediction performance of all quality attributes of pineapples with R^2 values of up to 0.94. Several machine learning algorithms including linear discriminant analysis, quadratic discriminant analysis, k-nearest neighbour, support vector machine, decision tree, and Naïve Bayes were applied for the classification of pineapple varieties. The results showed that the support vector machine achieved the best performance from the combination of optimal image parameters with the highest classification rate of 100 %.

Convolutional neural networks (CNN) were developed to determine the classification of pineapple varieties with the highest accuracy of 99 % via InceptionV3. The precision, recall, and F1-score demonstrate promising results with the values higher than 0.85 for all pineapple varieties. Multimodal data fusion based on three different CNN architectures including ResNet, VGG16, and InceptionV3 was designed for the classification of pineapple varieties with classification rate up to 92 %. Apart from that, a graphical user interface (GUI)-based software for determination of classification accuracy and quality prediction of the fruit is developed. The application of GUI using the CNN approach can also improve the predictive performance of the fruit classification collected in multi-batch image datasets. Hence, it is noted that the feasibility of infrared thermal imaging coupled with artificial intelligence approaches is a promising technique for assessing the variety classification and the quality parameters of pineapples during storage.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

SISTEM KECERDASAN BUATAN UNTUK KLASIFIKASI VARIETI NANAS DAN PENILAIAN KUALITI SEMASA PENYIMPANAN MENGGUNAKAN PENGIMEJAN TERMAL INFRAMERAH

Oleh

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Nanas adalah buah tropika yang sangat digemari kerana aromanya yang unik dan rasa manis. Pemantauan kualiti nanas adalah penting untuk mengawal selia pengendalian lepas tuai dan pengeluaran hasil yang betul. Dalam kajian ini, pengimejan terma inframerah digunakan untuk menentukan sifat kualiti buah, khususnya jumlah pepejal larut (TSS), kandungan lembapan, pH, perubahan warna, dan tekstur pada varieti yang berbeza berdasarkan pelbagai keadaan penyimpanan (suhu penyimpanan dan hari penyimpanan). Tiga jenis nanas telah digunakan dalam kajian ini iaitu MD2, Morris, dan Josapine. Sebanyak 1080 biji nanas segar pada peringkat masak Indeks 2 telah digunakan dalam kajian ini. Sampel disimpan pada tiga suhu penyimpanan yang berbeza iaitu di dalam bilik simpanan sejuk (5 °C), peti sejuk terkawal (10 °C), dan bilik makmal berventilasi udara (25 °C) dengan julat suhu ±2 °C dan kelembapan relatif 85 hingga 90 %. Bagi setiap varieti, 30 sampel telah dipilih secara rawak untuk pengumpulan data pada setiap selang tujuh hari (Hari 0, Hari 7, Hari 14, dan Hari 21). Imej terma nanas diperoleh pada tiga jenis varieti berbeza pada pelbagai keadaan penyimpanan berdasarkan hubungan sifat fizikokimia dan parameter imej. Dengan menggunakan kinetik peringkat pertama, nilai R^2 bagi perubahan kualiti nanas adalah antara 0.893 hingga 0.992. Hasil kajian juga menunjukkan bahawa sampel yang disimpan pada suhu 10 °C mempunyai jangka hayat yang paling lama berhubung dengan perubahan dalam ketegasan dan kandungan kelembapan buah. Analisis komponen utama digunakan untuk membangunkan model ramalan kuantitatif dan keupayaan pengelompokan tiga jenis nanas yang berbeza. Hubungan optimum antara semua parameter imej berjaya menerangkan keteguhan model kuasa dua separa terkecil (PLS) yang menunjukkan prestasi ramalan kualiti nanas yang baik dengan nilai R^2 sehingga 0.94. Beberapa algoritma pembelajaran mesin termasuk analisis diskriminasi linear, analisis diskriminasi kuadratik, jiran terdekat k, mesin vektor sokongan, pepohon keputusan dan Naïve Bayes telah digunakan untuk mengklasifikasikan variety nanas. Keputusan menunjukkan mesin vektor sokongan mencapai prestasi terbaik daripada gabungan parameter imej optimum dengan kadar pengelasan tertinggi sebanyak 100 %. Rangkaian saraf konvolusi (CNN) telah dibangunkan untuk menentukan klasifikasi varieti nanas dengan ketepatan tertinggi 99 % melalui InceptionV3. Ketepatan, ingatan semula dan skor F1 menunjukkan hasil yang baik dengan nilai yang lebih tinggi daripada 0.85 untuk semua jenis nanas. Gabungan data multimodal daripada tiga jenis model CNN menunjukkan hasil yang baik untuk penentuan kualiti nanas dengan kadar pengelasan sehingga 92 %. Selain itu, perisian berasaskan antara muka pengguna grafik (GUI) untuk penentuan ketepatan pengelasan dan ramalan kualiti telah dicipta. Aplikasi GUI menggunakan pendekatan CNN juga boleh meningkatkan prestasi ramalan klasifikasi buah yang dikumpul dalam set data imej berbilang kelompok. Oleh itu, adalah diambil perhatian bahawa kebolehlaksanaan pengimejan terma inframerah ditambah dengan pendekatan pintar buatan adalah teknik yang berkesan untuk menilai klasifikasi variety dan parameter kualiti nanas semasa penyimpanan.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ANN	Artificial neural network
ANOVA	Analysis of variance
CNN	Convolutional neural network
DBN	Deep belief networks
DCNN	Deep convolutional neural network
FFNN	Feed-forward neural networks
FN	False negative
FNN	Fully connected network
FP	False positive
GAN	Generative adversarial networks
GLCM	Gray level co-occurrence matrix
GUI	Graphical user interface
IoU	Intersection over Union
kNN	k-nearest neighbour
LDA	Linear discriminant analysis
LSTM	Long short-term memory networks
PCA	Principal component analysis
PLS	Partial least squares
PLS-DA	Partial least squares-discriminant analysis
QDA	Quadratic discriminant analysis
RBM	Restricted Boltzmann machines
RCNN	Region-based convolutional neural network
ReLU	Rectification linear unit
ResNet	Residual neural network

RMSE	Root mean square error
RMSEC	Root mean square error of calibration
RMSEP	Root mean square error of prediction
RNN	Recurrent neural networks
ROI	Region of interest
R^2	Coefficient of determination
SGDM	Stochastic gradient descent with momentum
SIMCA	Soft independent modelling of class analogy
SVM	Support vector machine
TN	True negative
TP	True positive
TSS	Total soluble solids

CHAPTER 1

INTRODUCTION

1.1 Background study

Pineapple is a tropical fruit that is native to the coastal lowlands of South America such as Columbia, Brazil, and Paraguay, which can either be consumed fresh or processed into various food products (Barretto et al., 2013). It is the third-ranked most widely cultivated tropical fruit in terms of economic production, after banana and citrus (Zainuddin et al., 2020). The pineapple market has been growing extensively due to the attractive aroma compounds and nutritional values as well as huge demand and competitive retail prices (Martínez et al., 2012). Pineapple is mainly cultivated in the tropical and sub-tropical regions due to the temperate climate and rainfall distributions. The top five pineapple producers worldwide in 2020 were reported consisted of Philippines (2.70 million tonnes), Costa Rica (2.62 million tonnes), Brazil (2.46 million tonnes), Indonesia (2.45 million tonnes), and China (2.22 million tonnes) (FAOSTAT, 2022). The crop can bear fruit at the early stage after flowering, allowing the yield production throughout the year (Shamsudin et al., 2009). The shelf life of pineapple can be prolonged by storing the fruit in specific conditions and storage temperature as well as specific treatment to avoid microorganism contamination (Ismail et al., 2018). In this context, a well-reasoned anticipation to transform perishable fruit into staple products with longer shelf life has been developed to reduce the qualitative quality deterioration of the fruit during storage.

Infrared thermal imaging is a non-destructive sensing technique that measures infrared energy emitted from the object's surface. The detected energy is converted by the camera into a thermal map called a thermogram. Infrared thermal imaging may be used not only for defect sorting but also for other quality attribute sensing because of its non-destructive ability. In agriculture, thermal imaging has wide applications in determining crop water stress, irrigation scheduling, pathogen and disease detection in plants, bruise detection and maturity evaluation of fruits, and yield estimation of fruit in the orchard. Due to this characteristics and functions, infrared thermal imaging has shown promising results in the determination of fruit quality such as apples (Badia-Melis et al., 2016), pears (Hahn et al., 2016), grapes (Ding et al., 2017), blueberries (Kuzy et al., 2018), and green citrus (Gan et al., 2018). Badia-Melis et al. (2016) successfully predicted the surface temperature over a pallet of apples whilst comparing packaging (plastic boxes and cardboard boxes) using thermal imaging technique. Kuzy et al. (2018) developed a thermal imaging system and explored its feasibility in detecting bruised blueberries non-destructively. In the same manner, Ding et al. (2017) obtained the classification abilities based on the alcoholic volatiles by thermal images of fresh, seriously decayed, and moderately decayed grapes with correct classification accuracies of 100 %, 93 %, and 90 %, respectively.

Thermal imaging technology has gone through a constant development process over the past decades. Starting with thermal cameras, which use differences in contrast for defect detection, imaging technology has advanced to increasingly precise thermal colour cameras. This has advantages for the food processing industry, where the fruits quickly change apart from the shorter development and modification cycles. There are numerous opportunities to integrate thermal imaging into portable, mobile, or desktop devices. In addition to the conventional method for quality inspection of fruit, thermal imaging has additional unique requirements that must be considered by the users to be applied in the real-life situation. The thermal imaging technology plays a major role in the temperature mapping of essential process and product in many industries and is gaining momentum in the agriculture and food industries. The non-contact, non-destructive, nature of thermal imaging along with the rapid online usability are the major reasons for the fast-growing demand for this technique in various fields. The researchers are exploring the potential of using thermal imaging in various processes in the agriculture and food industry due to its numerous advantages.

Nowadays, various artificial intelligence-based approaches such as machine learning and deep learning methods have been developed to quantify the quality and safety evaluation of different kinds of fruit. In this sense, the integration of infrared thermal imaging coupled with artificial intelligence could provide an efficient approach since the nature of the algorithm is easy to analyse and produce rapid results. In recent years, the advance of various data processing and hardware technologies exploited a rising trend in deep learning approaches. Deep learning is highly regarded as a technique with a strong ability to compute data and improve the performance of algorithms. As a branch of artificial intelligence, deep learning is capable to analyse a huge amount of data by providing more robust analyses with high performance on the thermal information. The role of deep learning in food-agriculture related tasks is hugely explored due to promising applications including food recognition (Cecotti et al., 2020; Cotrim et al., 2020), maturity estimation (Villaseñor-Aguilar et al., 2020), disease detection (Prabhakar et al., 2020), quality inspection (Guedes et al., 2020), fruit classification (Momeny et al., 2020), defect detection (Jahanbakhshi et al., 2020; Zeng et al., 2020), etc. In this regard, deep learning approach provides efficient and precise results compared to conventional and routine laboratory analyses. Hence, it offers promising potential to evaluate the variety classification and quality attributes of pineapples at different storage conditions to ensure the fruit is of high quality when reached the consumers.

1.2 Problem statement

Pineapple is an exotic fruit that is well valued due to its aroma, flavour, and juiciness. To date, there are many pineapple varieties with various colours, shapes, sizes, and flavours. Pineapple is a rather medium size compared to other tropical fruits, which consists of multiple fruitlets with a distinctive maturation pattern from the top part near the crown until the bottom part of the fruit (Montero-Calderón et al., 2010). Considering the fact that pineapple is a non-climacteric fruit, the quality changes of the fruit varies and are not uniform. Generally, different pineapple varieties have different unique traits and characteristics. For this reason, pineapples are evaluated based on physical, physicochemical, and chemical attributes of fruit with acceptable flavour and morphological characteristics. The composition of pineapple flesh might also vary between different varieties of the fruit. Nevertheless, the changes in pineapple attributes may easily cause quality deterioration and the undesirable losses are normally accumulated because of the destructive nature of the conventional analysis (Adiani et al., 2020; Priyadarshani et al., 2019). Therefore, the evaluation of quality attributes of different pineapple varieties is vital to ensure the fruit is of acceptable quality range.

Keeping appropriate and good quality fruit during storage has been a challenge to the pineapple industry. The main problem arises during the postharvest handling of pineapple in which the defects start to appear until several days after the fruit has been exported (Siti Rashima et al., 2019). This is one of the main issues in the pineapple industry since the fruit quality cannot be determined at an early stage by visual appearance during postharvest handling which can influence the choice and palatability of the consumers. Generally, visual inspection such as firmness, bruising, external defects, and colour changes are regarded as the key criteria for the customers to assess the quality of the fruit (Dittakan et al., 2018). These include texture, flavour, appearance, and chemical composition of the fruit that could influence consumer acceptability and preference (Padrón-Mederos et al., 2020). Several aspects such as postharvest handling and storage temperature could affect the quality and shelf life, as well as the sensory characteristics of the fruit during storage (Guimarães et al., 2018; Steingass et al., 2015). The fruit quality of pineapple may still deteriorate during storage due to various factors such as humidity, temperature, and water activity.

Although several studies have been conducted to detect quality attributes of pineapple, the methods are mostly destructive or minimally destructive. However, these methods may not be implemented efficiently due to the large volume of pineapple yield given their limitations in terms of accuracy and speed. In addition, some techniques also require human skill and experience for the fruit sorting as well as grading processes (Khatiwada et al., 2016). The development of a rapid, accurate and non-destructive technique for sensing the quality attributes of the fruit at different varieties is expected could resolve this problem. For this reason, advanced and non-destructive techniques specifically for pineapples are required which could determine the fruit quality without damaging the whole fruit. The integration of infrared thermal imaging with artificial intelligence techniques offers quality determinations of pineapple fruit in a rapid way. Hence, this study attempted to explore the potential of infrared thermal imaging driven by artificial intelligence-based approaches to determine the variety classification and quality attributes of pineapples during storage.

1.3 Significance of study

According to the Food and Agriculture Organization (FAO), the world population is estimated to reach 9.7 billion by 2050 which could intensify the global food production (FAO, 2002). Since the increase of the human population continues to increase, the food production must also keep pace with it to meet the future demand, especially for agricultural products (Frona et al., 2019). Recently, the pineapple industry has had a growing need for developing robust and efficient methods to be used in the quality determination of the fruit. Numerous fast and non-destructive methods have been used in tandem with the quality evaluation of pineapples. The current studies provide a low-cost and rapid way on the variety classification and quality evaluation of pineapple during storage using the infrared thermal imaging approach. These trends provide the motivation for the future possibility to adopt the artificial intelligence approach which has demonstrated reliable success in producing good quality fruit to the consumers.

Artificial intelligence methods are used to provide reliable results by means of any computational network leading to a rapid surge in the pineapple production. Without human intervention, artificial intelligence could be established for promoting automated handling systems to reduce the postharvest losses. As an added bonus, the artificial intelligence method is suitable to solve real-time situations by simulating the models through data training. For this reason, infrared thermal imaging techniques are coupled with artificial intelligence-driven methods to obtain rapid and objective detection of the sample. This study provides a non-destructive solution to overcome the problem of manual inspection which is prone to human errors and time-consuming. A baseline database has been established which could be utilised as a starting point for future work and practical deployment related to the pineapple as well as other fruits. Apart from that, the growth of wireless technologies has created more diverse applications for data collection. Thus, the overall advantages of artificial intelligence are encouraging for the potential uses towards efficient models, thereby further real-time monitoring for rapid detection of food and agricultural products.

1.4 Research objectives

The goal of this research is to develop an artificial intelligence system for pineapple variety classification and its quality evaluation at different storage days

(Day 0, Day 7, Day 14, and Day 21) and storage temperatures (5, 10, and 25 °C) using infrared thermal imaging. The specific objectives are:

i. To identify thermal image parameters of pineapples with respect to different varieties, storage days and temperatures.

ii. To determine physicochemical properties of pineapples with respect to different varieties, storage days, and storage temperatures using standard reference methods.

iii. To evaluate the model performance of variety classification of pineapples using conventional machine learning and deep learning methods.

iv. To develop graphical user interface for determination of classification accuracy and quality prediction of different pineapple varieties using deep learning algorithms.

1.5 Scope and limitations

This study is focused on classifying the pineapple fruit at three different varieties (MD2, Morris, and Josapine) which were tested at four storage time intervals (Day 0, Day 7, Day 14, and Day 21) during storage. The fruit samples were stored in three different storage temperatures (5, 10, and 25 °C) with relative humidity of 85 to 90 % throughout the experiment. The pineapples were harvested 13 months after planting and transported immediately to the Biomaterials Processing Laboratory, Universiti Putra Malaysia after harvest. The pineapple samples were harvested on the same day to avoid the seasonal variances in the physicochemical properties between the varieties. The pineapple images were captured under consistent lighting conditions in a laboratory room at a temperature of 25 °C. The imaging device used for image acquisition is a handheld infrared thermal imaging camera with 320 x 240 pixels infrared resolution. The crown/stem is included in the image analysis by considering it as the whole fruit despite different types of pineapple varieties. For the model development using the deep learning method, similar training, validation, and testing sample datasets are used for both single pre-trained CNN and multimodal data fusion. The application of GUI does not cover the remaining shelf life of the fruit since the implementation of the toolbox is focused only on showing the classification accuracy based on fruit variety and quality prediction of the fruit.

1.6 Thesis outline

This thesis content is organised into five chapters, which are presented as follows:

Chapter 1 describes the background study driving this work which highlights the pineapple cultivation, quality evaluation of the fruit, and the fundamental concept of infrared thermal imaging techniques. This chapter also outlines the research objectives as well as the scope and limitations of the study.

Chapter 2 provides a literature review of the cultivation and quality evaluation of pineapples. It also presents the application of infrared thermal imaging for quality evaluation and safety inspection of various food and agricultural products. This is followed by a detailed review of artificial intelligence system for fruit quality detection and classification. Previous studies relevant to this research were summarised and reviewed. This chapter discusses the fundamental concepts and mechanisms of deep learning for assessing pineapple quality.

Chapter 3 elaborates the methodology and various steps of data processing and analysis to determine the capability of infrared thermal imaging to evaluate the variety classification and quality changes of pineapples during storage. Image parameters were selected based on the feature extraction of pineapple images to develop prediction models for the quality detection of the fruit. Several machine learning algorithms were applied to develop classification models which discriminate the fruit according to the storage days and storage temperatures. It also describes the deep learning methods for the variety classification of pineapples based on storage days and storage temperatures. The model training and evaluation based on various CNN architectures using transfer learning for the variety classification of pineapples is discussed in detail. A multimodal data fusion of three different CNN models along with the weight information is combined to perform the fruit classification. This is followed by the implementation of a graphical user interface (GUI) for the determination of classification accuracy and quality prediction of different pineapple varieties.

Chapter 4 describes the results and findings obtained from each research objective. This work demonstrates the identification of image parameters of thermal images of pineapples in relation to different varieties, storage days, and storage temperatures. The physicochemical properties of pineapples were also investigated with respect to different varieties, storage days, and storage temperatures using standard reference methods. The best machine learning algorithm was determined based on the highest classification accuracy for both calibration and prediction datasets. The accuracy of fruit variety classification is enhanced by means of transfer learning and multimodal data fusion based on deep learning technique using three CNN architectures. This chapter also demonstrates an application of a graphical user interface-based toolbox for determination of classification accuracy and quality prediction of different pineapple varieties. The toolbox allows the model training and selection based on the image datasets of the fruit.

Chapter 5 summarises the conclusions and achievements of this research, along with the recommendations for future research studies.

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