ARTIFICIAL NEURAL NETWORK MODELLING OF DRYING KINETICS OF CANTALOUPE IN A MICROWAVE-CONVECTIVE DRYER

By

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This Thesis is dedicated to my Parents.

For their endless love, support, and encouragement

ABSTRACT

Drying is an essential processing method widely used in the food industry to extend shelf life. In recent years various techniques for modelling the drying process have been investigated. One of the emerging tools used for predicting the drying parameters is Artificial Neural Networks (ANN). In this study, an attempt was made to develop different types of ANNs – Feed-forward networks (FNN) and Long short term memory recurrent networks (LSTM), and to compare the trained models with traditional mathematical modelling techniques. Cantaloupe was used as the drying material.

In the first part, FNN and LSTM were trained using 70% of data retrieved from a previous study of cantaloupe slices dried in a microwave convective dryer. The networks were used to predict the moisture ratio and product temperature. The number of hidden layers, number of neurons per hidden layer, and the batch size were varied to experiment with different architectural configurations of the models. The trained networks were then tested on the remaining 30% dataset to evaluate the fit of the model. The statistical indices used to compare the performance of different networks were Mean Squared Error, Mean Absolute Error, and Coefficient of Determination. The study achieved promising results with the best network having a coefficient of determination of 0.997 for the test set. The FNN networks were found to perform better than LSTMs. The models gave a better estimation of moisture ratio than product temperature.

In the second part, cantaloupe slices were dried in the microwave convective dryer for different air temperatures and initial microwave power densities (IMPD). The drying behaviour was modelled using various mathematical models and the trained ANN model developed in the first part. The colour change, hue and chroma of the final dried product were analyzed. Moreover, the

phenolic content and the antioxidant activity of the end product was estimated. The results showed that the two-term equation was best in predicting the moisture ratio as a function of time. Also, the mathematical models were found to perform better than the ANN model.

RÉSUMÉ

Le séchage est un procédé largement utilisée dans l'industrie alimentaire pour augmenter la durée de conservation des denrées périssables. Au cour des dernières années, plusieurs techniques permettant de modéliser le séchage ont été étudiées. Parmi ceux-ci, l'un des outils émergents est le réseau de neurones artificiels (RNA). Dans cette étude, différents modèles mathématiques conventionnels, des RNA à action directe (feed-forward, FFN) et des Réseaux récurrents à mémoire à court terme (LSTM), ont été développés et comparer pour décrire la cinétique de séchage de rondelles de cantaloup.

Dans un premier temps, des modèles FNN et RNN ont été construits en utilisant 70% des données obtenues lors d'une étude précédente sur des rondelles de cantaloup séchées dans un séchoir à convection et à micro-ondes. Les réseaux ont été utilisés pour prédire les changements dans la teneur en eau et de la température du produit en fonction du temps de séchage. Différentes configurations architecturales des modèles ont été étudiées et comparées et fonction du nombre de couches cachées utilisé, du nombre de neurones par couche cachée et de la taille du lot. Par la suite, les réseaux entraînés ont été validés en utilisant les 30 % de données restantes. Les paramètres statistiques utilisés pour comparer leurs performances étaient : l'erreur quadratique moyenne, l'erreur absolue moyenne et le coefficient de détermination. Les résultats obtenus étaient excellents puisque la meilleure architecture de réseau avait un coefficient de détermination de 0.997 pour l'ensemble du test. Les réseaux FNN se sont avérés plus performants que les LSTM. De manière générale, les modèles ont donné de meilleures valeurs de teneurs en eau que de la température du produit.

Dans la seconde partie, des essais en laboratoire ont été effectués pour valider les modèles. Lors des essais, des tranches de cantaloup ont été séchées dans le séchoir à convection et à micro-ondes, et cela, à différentes températures de l'air et densités de puissance micro-ondes initiales (IMPD). Le comportement de séchage a été modélisé à l'aide de divers modèles mathématiques et des modèles RNA entraînés et développés dans la première partie. Le changement de couleur, la teinte et le taux de saturation de la couleur du produit séché ont été analysés et comparés. De plus, la teneur en phénol et l'activité antioxydante du produit final ont été estimées. Les résultats ont montré que le modèle mathématique conventionnel à deux termes était le meilleur pour prédire la teneur en eau en fonction du temps de séchage. De façon générale, les modèles mathématiques conventionnels se sont avérés plus performants que le modèle RNA.

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CONTRIBUTION OF AUTHORS

The work reported in this thesis was performed by Amol Kaur Randhawa under the supervision of Dr. Vijaya Raghavan of the Department of Bioresource Engineering, Macdonald Campus of McGill University, Montreal. This thesis is manuscript-based in accordance with the guidelines presented by Graduate and Postdoctoral Studies of McGill University and consists of two research manuscripts (Chapter III and IV). Chapter I, II and V consists of the introduction, review of literature and summary, respectively.

The following are the manuscripts prepared for submission:

Chapter III

Randhawa, A.K., Iheonye, A., Gariépy, Y. & Raghavan, G.S.V., Study of two ANN approaches for predicting drying kinetics of cantaloupe in a microwave convective dryer.

Chapter IV

Randhawa, A.K., Iheonye, A., Gariépy, Y. & Raghavan, G.S.V., Comparative study of mathematical and ANN modelling for microwave convective drying of cantaloupe.

For the manuscripts, I designed the experiments, developed the computer code, conducted the experiments and wrote the manuscript. Dr. Raghavan overlooked the planning of research activity, provided scientific suggestions, and helped in editing of the manuscripts. Mr. Iheonye helped with implementation of the computer code, designing the experiments and in editing of the manuscripts. Mr. Gariépy provided the technical assistance for carrying out the experiments, helped in designing the experiments and editing of the manuscripts.

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CHAPTER I

INTRODUCTION

1.1. Introduction

Food loss and waste is a growing global issue, posing a threat to food security, food safety, the economy and environmental sustainability. According to FAO (2015), food wastage occurs at the production and supply stage in developing countries and on the retail stage in developed countries (Scialabba, 2015). Food wastage not only ruins the resources used to produce food like water, agricultural land but also causes pollution. One way to combat the food loss problem is to dry them into by-products with added value.

Cantaloupe is a widely consumed fruit because of its pleasant aroma and fresh taste. Several studies have reported cantaloupe as an antioxidant-rich fruit with anti-inflammatory properties. Moreover, due to high amounts of nutrients like folic acid, zinc, iron, carotenoids it poses myriad of health benefits. Cantaloupes are 90% water, thus, have a very short shelf life. Drying is one of the processing methods used to produce dried cantaloupe that may be eaten as a nutritious snack or used in desserts. However, drying changes the quality and appearance of fruit in many ways. The nutritive value of the fruit decreases, as high temperatures can cause degradation of vitamins and minerals. Therefore, it is important to study the process of cantaloupe drying using various suitable technologies.

Predicting the drying kinetics of agricultural products under different conditions is crucial to understand, scale up, or simulate the drying process without carrying out new experiments. Moreover, it helps to optimize the operating conditions and improve the drying equipment to minimize the cost. Also, accurate prediction of the product's temperature and moisture distributions are required to better describe the drying behaviour of various food materials. Moreover, comprehending the relationship between these food properties and the operational parameters of the dryer could help in predicting and controlling real-time changes in food quality. However, due to complex, non-linear transformations taking place throughout the process, it is difficult to model this process (Sabarez, 2015).

Recent research has shown significant advances in modelling and precise estimation of drying parameters using Artificial Neural Networks (ANNs) (Dash et al., 2020; Hernández, 2009; Raj & Dash, 2020; Singh, 2011). Unlike analytical or mathematical modelling methods, ANNs do not require prior understanding of the mathematical relationship between the food properties and drying parameters. They learn the underlying relationship while iterating through the training examples (Hassoun, 1995). Because of their ability to account for non-linearities, many researchers have successfully applied ANNs to forecast the drying kinetics parameters. Feedforward neural networks (FNNs) and recurrent neural networks (RNNs) have been used to predict the drying process adequately and precisely (Çakmak & Yıldız, 2011; Khazaei & Daneshmandi, 2007). Many researchers have investigated both ANN methods to simulate the drying kinetics of various products such as apple (Nadian et al., 2015).

As RNNs are capable of forecasting time series data, this powerful technique has been exploited to effectively forecast one step ahead moisture content in several studies (Lertworasirikul & Tipsuwan, 2008; Samadi et al., 2013). Further, RNNs can be used to predict the various food quality-sensitive points, such as determining the product temperature for future time steps. These sets of time sensitive data are priceless inputs for drying system control.

Another area of ANN research is to determine how much data is sufficient to optimally train a neural network to accurately model the drying kinetics of food product. Numerous studies have trained and validated ANNs with small datasets (Marić et al., 2020; Watanabe et al., 2013). With insufficient data, the variance between the predicted output and the ground truth data is high. To avoid this undesirable outcome, researchers strive to feed their network with an abnormally large dataset. However, if that break-even point (the minimum size of training examples needed for the model to converge at optimal weights) is determined, it could reduce the computational cost associated with training the network. Determining the minimum data size could also lead to cost savings when acquiring sensors and data acquisition system used for capturing drying and system parameters, which would make up the pool of training data.

1.2 Hypothesis

Drying of fruits and vegetables is essential to reduce food losses caused by their highly perishable nature. Microwave convective drying is an emerging technique being used increasingly to achieve faster and more uniform drying of materials with high heat and mass transfer rates and better product quality. Since, drying is a complex, dynamic and nonlinear process, modelling is vital to understand the behaviour of materials in a drier and extending its application to the food industry. Using Artificial Neural Networks (ANNs) to predict the drying kinetics is a better way than the conventional mathematical methods. Feed forward Neural Networks (FNNs) can provide a precise prediction of the drying kinetics of the food materials. Moreover, with dynamic ANN models i.e. Recurrent Neural Networks (RNNs) superior forecast of the time sensitive parameters like the moisture ratio and product temperature can be achieved.

1.3 Objectives

The main objective of this research project was to apply Artificial Neural Networks to predict the drying parameters of cantaloupe, to assess the efficacy of FNNs and RNNs and validate the models developed with new experimental data. The investigations of my research were:

1. To develop ANN model for predicting drying parameters of cantaloupe in a microwave-convective dryer
    i. To model the moisture ratio of cantaloupe undergoing microwave convective drying using LSTM recurrent and feed forward neural networks
    ii. To model the surface temperature of cantaloupe during microwave convective drying using LSTM recurrent and feed forward neural networks.
    iii. To investigate the effects of the size of training data on the prediction accuracy for the drying parameters of cantaloupe dried using a microwave convective dryer

2. To model the drying kinetics of cantaloupe slices in a microwave convective dryer
    i. To investigate the drying behavior of cantaloupe in a microwave convective dryer.
    ii. To validate predictive mathematical models and ANN model relating changes in moisture ratio as a function of time
    iii. To analyze the colour, phenolic content and antioxidant activity of the dried product

CHAPTER II

LITERATURE REVIEW

2.1 Overview

Food security is defined as everyone having physical, social, and economic access to enough, safe, and nutritious food that always meets their dietary needs and food preferences, in order to live an active and healthy lifestyle (Pinstrup-Andersen, 2009). According to a 2014 study, approximately one in every ten households, or 12.3 percent of households in the United States and 6.0 percent of households in Canada, were affected by food insecurity (Tarasuk et al. 2014). Moreover, prior to the COVID-19 pandemic, a 4.8 percent increase in food insecurity was observed in 2019 (Statistics Canada, 2021), placing Canada 37th out of 41 developed countries in terms of food security and nutrition (UNICEF Canada, 2019b). A Hunger report (Food Banks Canada, 2021) stated a 20.3% increase in food bank visits made by Canadians indicating an increase in food insecurity as a result of the pandemic. Canada is expected to have the lowest rates of food security by 2021, when the World Bank classifies Canada as a high-income country (The World Bank, 2021). To address food security issues in developed and developing countries, the first attempt should be reducing food losses.

Consumer demand for fresh, healthy, and nutritious food has increased in synch with population growth. While sufficient food is produced daily to feed the world's population, due to lack of technology the food produced does not reach those in need, making food waste a major challenge for all food processing sectors to overcome. The total greenhouse gas emissions come not only from power generation machinery and transportation vehicles, but also from the decomposition of food waste (FAO, 2013). Food loss also has huge impact on water and land resource degradation.

As a result, carbon footprint of food waste has been estimated to be equivalent to 3.3 billion tonnes of CO_2 per year.

Throughout the food production and distribution processes, losses occur at various stages. The data in Figure 2.1 depicts the distribution of food loss by type of food, as reported in the State of Food and Agriculture report (FAO, 2019). Fruits and vegetables had the second highest percentage of food loss among all food groups, owing to their perishable nature and short shelf life. The percentage of loss is calculated based on the physical amount lost divided by the amount of production for each commodity group.

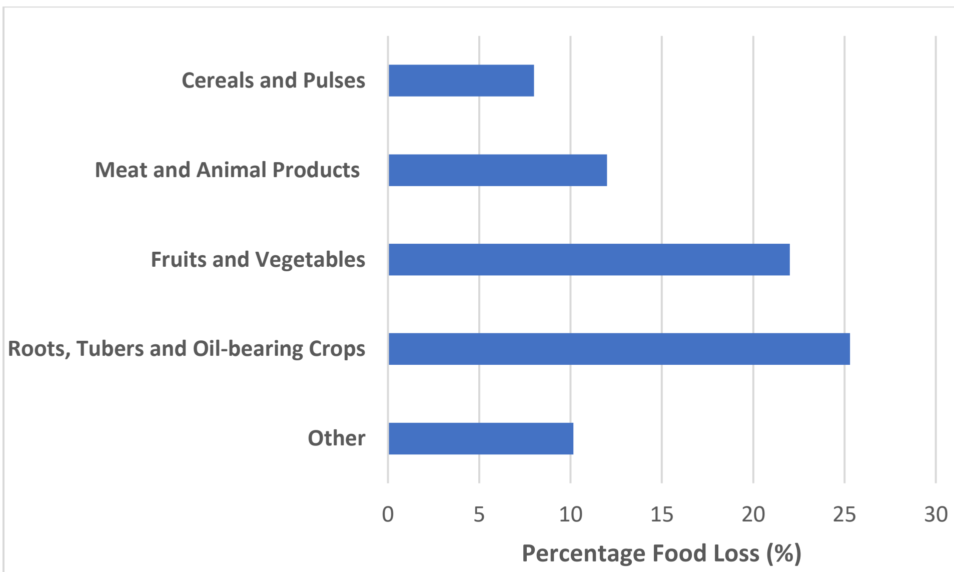


Figure 2.1 Percentage of food loss for various commodity groups

At the moment, the global market for processed foods is worth approximately $7 trillion, and it is steadily growing (Wilkinson & Roch, 2006). Globalization and industrialization have been critical factors in the development of food processing industries in various countries. According to a 2018 UNIDO Industrial Statistics Database analysis, food processing is a favourable component of the manufacturing sector in Canada (UNIDO, 2018). Across the world, conventional food processing techniques such as drying, freezing, chilling, pasteurisation, and chemical preservation are comprehensively used. Scientific progress and advancements are required, assisting in the evolution of existing technologies.

2.2 Cantaloupe

Fruits are an important component of human diet. They are a source of large variety of nutrients. Cantaloupe belongs to the cucurbit family of plants (Cucurbitaceae) which is packed with vitamin A, vitamin C, potassium, carotenoids, and fibre. Carotenoids are responsible for the orange-yellow pigment on the cantaloupe pulp. β-carotene is the main carotenoid present, followed by β-cryptoxanthin and lutein (Esteras et al., 2018). As a result of the antioxidant action by carotenes, these phytochemicals help fight diseases like asthma, diabetes, and cancer. (Ismail et al., 2010). Moreover, other essential acids such as benzoic, vanillic, and trans cinnamic acid are present (Kolayli et al., 2010), which have been linked to prevention from cardiovascular diseases, acne, and oral cavity cancers (Key et al., 2004; Li et al., 2021). Antioxidants like zeaxanthin and lutein found in cantaloupe have been proven to protect the eye and disarm the free radicals in the retina, decreasing the chances of vision loss (Abdel-Aal et al., 2013). Hence, because of myriad of health benefits and distinct fresh flavour, it is widely consumed all over the world. Unfortunately, fresh cantaloupes have a short post harvest life, lasting just one or two weeks under ambient conditions or even under refrigeration (Lamikanra et al., 2003). Hence, adoption of preservation techniques to increase shelf life, for making product marketing easier, is pertinent.

2.2.1 Drying of cantaloupe

Various drying methods have been used to decrease the moisture content of cantaloupe in the food industry. Chayjan et al. (2012) conducted the hot air drying of cantaloupe for different levels of air temperatures and air velocities. He found that the air temperature had more pronounced effect on drying time. Also, the results indicated that energy consumption increased with higher air velocities. Other studies investigated foam mat drying of cantaloupe. Li et al. (2021) carried out a study to produce highly stable powder for cake icing from cantaloupe pulp using foam mat drying. The Page equation was successfully used to model the drying behaviour. Salahi et al. (2015) reported two falling rate periods for foam mat drying of cantaloupe. They also demonstrated that increasing drying temperatures and decreasing foam thickness reduced the drying time. Solval et al. (2012) successfully used spray drying technology to produce cantaloupe juice powders. Amer & Albaloushi (2019) developed a solar dryer with photovoltaic modules to dry cantaloupe slices. This study demonstrated that using solar dryer significantly reduced the drying time compared to open sun-drying.

Some authors reported on drying of other parts of cantaloupe such as peel and seeds. Sroy et al. (2017) freeze dried the melon peel and assessed its nutritional attributes. The researcher stated significant reduction of phenols and retention of antioxidants after the drying process. Gulzar et al., 2017 dried melon seeds using a vibro-fluidized bed dryer. Faster drying rates were achieved at higher temperatures.

2.2.2 Quality of cantaloupe

The quality of processed cantaloupe can be assessed by measuring the phenolic content, the antioxidant activity along with physical properties such as colour. The change in colour is an indirect indicator of quality of the processed product. Numerous studies have been found that report on the colour of cantaloupe treated with methods such as ozone treatment and active packaging, to extend its shelf life. Toti et al. (2018) studied the changes in the colour of ozone treated cantaloupe stored for 13 days at 6°C. The ozone treated samples showed very little change in the colour parameters over the storage period. In another study by Kamaruddin et al. (2014) the colour of cantaloupe slices packed using polypropylene and low density polyethylene (LDPE) films were monitored. The Hue angle and Chroma was examined to evaluate the effectiveness of the two packaging systems in maintaining the quality of fruit. It was reported that the LDPE film was effective in preventing discolouration and browning of the fruit. Some studies were found that delineated the changes in the cantaloupe colour after drying. In a study by Korsrilabut et al. (2010) colour was one of the parameters used to assess consumer acceptance of osmotically dehydrated cantaloupe slices. A recent study by da Cunha et al. (2020) investigated the effectiveness of ethanol, ultrasonic and vacuum pre-treatments prior on convective drying of cantaloupe. The phenolic compound, carotenoid content and colour parameters were used to determine the overall quality of dried samples. A reduction in the quality associated with the parameters was observed. However, samples immersed in 50% ethanol solution showed the best retention of nutritional compounds.

Few studies were found where chemical properties such as phenolic and antioxidant content were measured for osmo-dried melon. Phisut et al. (2013) studied the effect of various pre-treatments of osmotic drying on the phenol and antioxidant content of cantaloupe. The phenolic content and antioxidant activity was seen to reduce as compared to the fresh fruit after the drying treatment. The possible reason stated was leaching of the bioactive compounds into the soaking medium. Naknaen et al. (2016) also analyzed the concentrations of phenolic and antioxidant activity for two different types of osmotic solutions. No literature was found on the estimation of chemical qualities of microwave convective dried cantaloupe. In a study by Alcade-Garcia, F (2020) the nutritional properties of cantaloupe in a microwave-convective dryer were reported. The trials with longest drying time reported significant degradation in the phenolic and antioxidant contents.

Some researchers reported on the nutritional properties of treated cantaloupe juice. Fundo et al. (2018) measured the changes in vitamin c, phenolic content and total antioxidant activity for ozone processed melon juice. For varying levels of ozone exposure, they found an increase in phenolic content and a decrease in antioxidant activity. Total carotenoids were found to be the most degraded bioactive compound after ozone treatment. Hashemi et al. (2019) studied the effects of thermal treatment by microwave heating and ohmic heating of cantaloupe juice. Their results indicated reductions of vitamin C, phenolic and carotene contents in thermal treated juice when compared to the fresh ones.

2.3 Drying

Drying, or dehydration is one of the oldest and most eminent unit operations in the food preservation industry. The essence of drying is to reduce the moisture or water activity of the solid being dried, to increase shelf life and achieve better quality (Michailidis & Krokida, 2014).

2.3.1 Dryers

The choice of dryer type affects the final quality of product, drying time and cost of operation. Hence, choosing the appropriate dryer is pertinent. The industry currently uses various dryers like, hot air dryers, vacuum dryers, fluidized bed dryers, tunnel dehydrators, microwave dryers, infrared dryers, heat pump dryers, drum dryers, sun dryers and freeze dryers (Mujumdar, 2006).

2.3.1.1 Convective dryers

Various industries, like agricultural, chemical, paper, and textile, employ dryers to reduce the moisture content of various kinds of materials (VP, 2020). Around 85% of the dryers used in these industries are convective dryers (Zarein et al., 2015). In this dryer, the process of heat and mass transfer occurs between the circulating air and the food material. Heat is transferred from the hot air to the product through convection. Simultaneously, mass transfer of moisture occurs to the product source through conduction and then to the circulating dry air. These types of dryers offer several advantages like increased shelf-life, ease of operation, economical, low maintenance (Calín-Sánchez et al., 2020).

Many researchers have successfully applied, this technique to several fruits, vegetables, and herbs. Tzempelikos et al. (2014) studied quince fruit undergoing convective drying at various temperatures and air velocities. They reported that increasing the temperature and velocity of drying air significantly increased the rates of mass and heat transfer, resulting in decreased drying time. However, increasing the air velocity beyond a certain value had no effect on the drying time. Another study by Seiiedlou et al. (2010) for convective drying of apples reported a decrease in drying time as a result of increase in air temperature. Both the drying air temperature and velocity influenced the time to reach equilibrium moisture content.

However, this drying method does not come without disadvantages. The final dried product has decreased antioxidant activity, lower rehydration capacity, reduced porosity, and significant colour changes as compared to the other drying techniques (Deng et al., 2018; Si et al., 2016; Tian et al., 2016). Moreover, the longer drying times needed during hot-air drying can cause serious damage to physical properties of the material (İzli et al., 2014).

2.3.1.2 Microwave dryers

The term “Microwave” refers to rapidly oscillating, perpendicular electrical and magnetic fields, with frequencies in the range of 0.3 Hz to 3 GHz. The microwave systems for industrial purposes operate at frequencies of either 915 MHz or 2450 MHz (Fu et al., 2017). The penetrating microwaves heat the food by conversion of electromagnetic energy to thermal energy. The two mechanisms responsible for energy conversion are dipolar rotation of polar molecules and ionic conduction. When the microwave energy enters the food material, water, a typical dipolar molecule reverses direction constantly to align with the alternating electric fields. This movement results in internal friction which generates thermal energy. Any other ionic species also migrate and cause the temperature of the material to rise. A device called magnetron is used to generate these electromagnetic waves (Mello et al., 2014).

The dielectric properties of the dried product, especially the dielectric constant and dielectric loss, influence the heating behaviour. The ability of a material to induce polarisation in response to applied electrical energy is defined by the dielectric constant. The amount of microwave energy converted to thermal energy is determined by the dielectric loss. Together these indicators influence the dissipation factor, which helps describe the penetration of microwaves in the target material. The greater a material's dissipation factor, the more microwave energy is dispersed as thermal energy (Kalla, 2017). Other factors influencing microwave heating are the frequency and power of the microwave, product composition, sample size and thickness (Beigi & Torki, 2020; Wang et al., 2014; Wäppling-Raaholt & Ohlsson, 2009).

This technique offers various advantages with minimum effects on the food quality (Puligundla et al., 2013). Authors have reported microwave dried product to have low colour changes (Ozkan et al., 2007; Sarimeseli, 2011), and good odour/flavor retention (Rayaguru & Routray, 2011).

Microwave drying has been investigated for various kinds of products such as strawberries (Raghavan & Silveira, 2001), green pepper (Darvishi et al., 2014), basil (Demirhan & ÖZBEK, 2010), mushroom (Lombraña et al., 2010), banana (Omolola et al., 2014) and pomelo (Yildiz & İzli, 2019), and many more.

2.3.1.3 Microwave assisted drying

High operating temperatures and case hardening are the key drawbacks of the traditional convection drying. The exposure to elevated temperatures results in shrinkage and alteration of product structure. Furthermore, the extended drying times may result in the deterioration of the nutritional and qualitative properties of the material, and increased power consumption.

However, microwave heating alone may yield to non uniform heating of food, which tends to form hot or cold spots within the material. Hence, using these drying methods individually, results in a product of degraded physical appearance and reduced nutritional value (Zhang et al., 2006).

However, when microwave drying and convective drying are used together, the combination is synergistic. The blend of microwave and convective drying allows to combine the advantage of both methods while overcoming some of their limitations (Gaukel et al., 2017). In this approach, the hot air is blown into the microwave chamber allowing the product's outside moisture to be removed, while the microwaves' volumetric heating accelerates moisture transfer from the centre to the surface. It has been validated that, addition of microwave energy to convective drying results in faster drying rates, improved product characteristics and better energy efficiency (Changrue et al., 2006).

Several authors have validated the reduction of drying time in products like tomato slices, (Izli & Isik, 2015; Workneh & Oke, 2013), okra (Kumar et al., 2014) and kiwi (Pham et al., 2018). Product quality parameters investigated which showed improvement were colour and sensory attributes for grated carrots (Arikan et al., 2012), cranberries (Sunjka et al., 2004) and apricots (Albanese et al., 2013).

2.3.2 Drying kinetics modelling

Drying conditions have a significant effect on the quality of product and on the efficiency of the process. Modelling is the primary tool used to understand the behaviour of material in a dryer and to optimize the conditions.

Monitoring the moisture ratio (MR) is crucial to establish the safe levels for safe storage and for controlling the microbial growth and is typically used to describe the drying kinetics (Zambrano et al., 2019). The moisture ratio is defined by the following equation,

$$MR = \frac{M - M_e}{M_o - M_e} \tag{2.1}$$

Where, M is the moisture content at any time t, M_o is the initial moisture content, and M_e is the equilibrium moisture content. Several published models have been used to describe the thin layer modelling of various fruits and vegetables. These models are classified as either theoretical, semi-theoretical, and empirical (Parti, 1993). The theoretical models consider the shape of food and are based on the internal force of moisture transfer. The semi- theoretical and empirical models are usually derived from the Fick's law of diffusion and consider the external force responsible for moisture transfer. (Da Silva et al., 2014; Kaleta & Górnicki, 2010). Commonly used empirical and semi theoretical models are given in Table 2.1. The constants in these equations have limited significance since the fundamentals of the drying process are neglected for designing the empirical equations (Ertekin & Firat, 2017). These equations are most commonly used to describe the drying kinetics as they give a better understanding of the experimental data (Onwude et al., 2016).

Table 2.1 Commonly used semi theoretical and empirical models

Model Name	Model Equation	Reference
Lewis	$MR = exp(-kt)$	(Lewis, 1921)
Page	$MR = exp(-kt^n)$	(Agrawal & Singh, 1977)
Logarithmic	$MR = a\ exp(-kt^n)$	(Xanthopoulos et al., 2007)
Henderson and Pabis	$MR = a\ exp(-kt)$	(Hendreson & Pabis, 1961)
Wang and Singh	$MR = 1 + at + bt^2$	(Wang & Singh, 1978)
Two-term	$MR = a\ \exp(-k_o t) + b\ \exp\ (-k_1 t)$	(Henderson, 1974)
Two-term exponential	$MR = a\ \exp(-kt) + (1 - a)\ \exp\ (-kat)$	(Sharaf-Eldeen et al., 1980)
Simplified Fick's differential equation	$MR = a\ \exp\ (-c(\frac{t}{L^2}))$	(Sacilik & Elicin, 2006)

Recently, over the past few years deep learning techniques such as Artificial Neural Networks have been studied to predict the drying kinetics of food.

2.3.3 ANN application for drying of cantaloupe

To the best of my knowledge, published literature on drying kinetics and application of artificial neural networks for modelling of cantaloupe are scarce. Kaveh et. al. (2018) applied ANN, as well as an ANFIS (Adaptive Neuro-Fuzzy Inference System) model to forecast drying characterises for convective drying of cantaloupe, potato, and garlic. Their inputs for estimating moisture diffusivity and energy consumption were product type and drying air parameters. For predicting drying rate and moisture ratio, drying time was also used as an input, in addition to the previous input variables. The Bayesian regularization (BR) and Levenberg-Marquardt (LM) optimizers were used for training the ANN models. The activation functions used to establish the best network structure were sigmoid, tangent of sigmoid, and Purelin. It was reported that the neural network models gave an acceptable prediction of the output. However, prediction obtained from the ANFIS models were found to be more accurate than those obtained from ANN (Kaveh, Sharabiani, et al., 2018).

Zadhossein et al. (2021) investigated the energy and exergy parameters using ANN and ANFIS models for microwave drying of cantaloupe of various thicknesses. In this case, better prediction of the thermodynamic parameters were achieved with the ANFIS models.

In another work, Kaveh et. al. (2018) reported fluidized bed drying of cantaloupe seeds. They developed several ANN models based on experimental data sets obtained for pistachio, squash, and cantaloupe seeds drying. The models were able to predict moisture diffusion and specific energy consumption as a function of air temperature, air velocity and product type. The backpropagation, Bayesian regularisation (BR) and Levenberg-Marquardt (LM) learning algorithms were used. They reported better prediction using the neural network models compared to the mathematical models (Kaveh, Chayjan, et al., 2018).

To the best of my knowledge, current literature focused on comparing the effectiveness of ANFIS to ANN, in predicting the drying kinetics of Cantaloupe. The only study that compared different ANN techniques was applied to Cantaloupe dried in a fluidized bed (Kaveh et. al., 2018). However, there has been no published work that compared the performance of an FNN to an RNN, in predicting the drying kinetics of Cantaloupe, dried in a microwave-assisted convective dryer.

2.4 Artificial neural network

Artificial Neural Network, loosely modelled after the biological neuron, is one of the most popular machine learning techniques. With the foundation of Artificial intelligence, this technique has taken over every aspect of todays life (Mishra & Srivastava, 2014). It is used to describe various physical phenomenon, clustering and forecasting problems because of its ability to learn from system patterns. Moreover, it is capable of generating meaningful solutions from imprecise data that contains errors and discrepancies, or is incomplete (Khashei & Bijari, 2010). Thus, it is being used increasingly to model and solve complex problems that are difficult to solve using traditional approaches.

2.4.1 Anatomy of neural network

A neuron or node is an information processing unit that is fundamental to the operation of neural networks. These nodes are combined to form a powerful network using 5 components listed below (Chollet, 2021; Dongare et al., 2012).

1. A set of *synapses* or *connecting links*, each of which is characterized by a weight or *strengths* of its own.
2. An *adder* for summing the input signals, weighted by the respective synapses of the neuron.
3. An *activation function* for limiting the amplitude of the output of a neuron. The activation function is also referred to in the literature as a *squashing function* in that it squeezes (limits) the permissible amplitude range of the output signal to some finite value.
4. A loss function or cost function; and
5. An optimizer

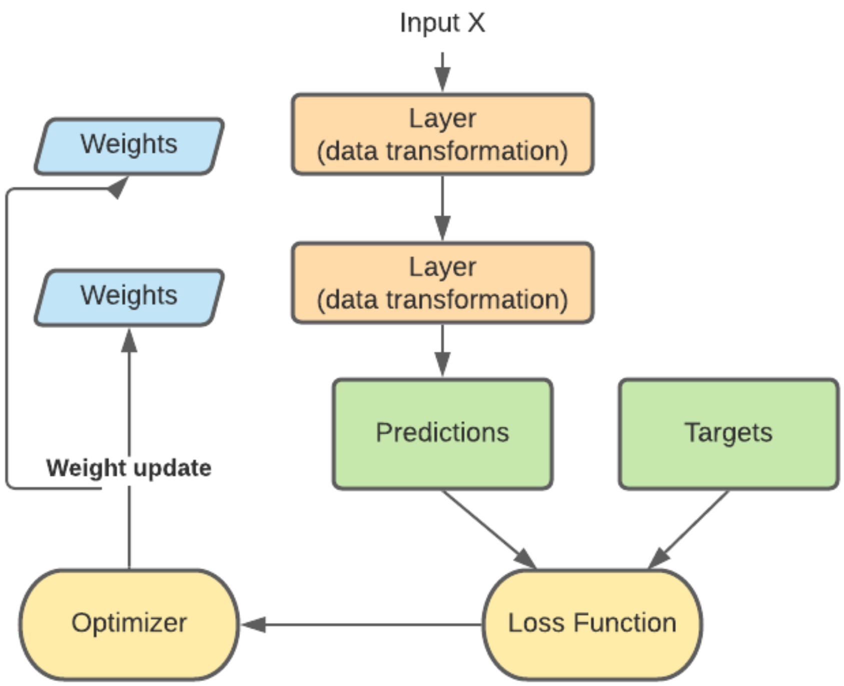


Figure 2.2 Learning algorithm of a neural network adapted from Chollet (2021)

The basic learning algorithm of neural network is given in Figure 2.2. The training parameters are fed into the input neurons, which are then processed by the hidden layers to produce a prediction through the output layer that estimates the error between predicted and target values. The error for a single example is the loss function and the average of the loss function for a number of examples is the cost function. At the end of each forward pass, the optimizer carries out a process known as backpropagation. During this step the weights associated with each neuron is updated using the gradient of the cost with respect of the current weight. This iterative process continues till the cost function is minimized and the network converges at a global minimum. Each complete cycle of feeding the samples and adjustment of synaptic weights is called an epoch (Da Silva et al., 2017).

The network architecture, the learning algorithm, and the activation functions used in the network all play important roles in network performance. Various activation functions and different learning algorithms for ANNs are discussed in subsequent sections.

2.4.2 Activation functions

Activation function controls the output from each neuron of the neural network. In other words, the activation function decides the neuron's operational firing rate. Depending on the type of problem or process being monitored, linear or non-linear functions can be used (Liu & Kang, 2017). Thus, the activation function chosen has a considerable impact on the neural network's performance. Moreover, it introduces nonlinearity in the model, otherwise it will just be a simple linear regression problem (Koçak & Şiray, 2021). The commonly used functions: sigmoid, hyperbolic tangent and ReLU are discussed below.

2.4.2.1 Sigmoid function

Sometimes referred as the logistic function, sigmoid function is a nonlinear function, typically used in shallow neural networks or in the output layer. This was considered as the most widely used transfer function for feed forward networks. It is given by the equation

$$f(x) = \frac{1}{(1 + exp^{-x})} \qquad 2.2$$

The output values for sigmoid lie between zero and one. The fixed output range make it a good classifier and is used to predict probability based outputs (Nwankpa et al., 2018).

However, researchers have indicated that this well-known transfer function is difficult to train because of small derivative which makes it difficult to update the weights when the network has a greater number of layers (Xu et al., 2016).

2.4.2.2 Hyperbolic tangent

The hyperbolic tangent function is an S shaped function, and the output of tanh lies between -1 and 1. The output values are clearly rescaling of the sigmoid function

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad 2.3$$

However, the tangent function increasingly became the preferred function due to improved performance. It is better than logistic function in a way that the negative values will be mapped close to -1, zero values as zero and positive values close to the main advantages of this function are that the derivative is larger than that of sigmoid, the loss can be minimised faster, and the model converges (Montavon et al., 2012). Chen et al. (2001) successfully applied this transfer function to model the drying time and quality parameters of osmotic drying of blueberries.

2.4.2.3 ReLU function

In this approach, the ReLU function returns the input itself for a positive value and 0 for negative value. Due to simple mathematical calculations involved, this function is computationally inexpensive. Moreover, the problem of saturation of gradient is avoided. Faster and effective training of deep neural networks with complex data is the advantage with this activation function.

$$f(x) = max(0, x) \tag{2.4}$$

Jin, Yin, et al. (2021) used ReLU in hidden layers of neural network predicting the drying time, temperature and germination rate ratio of thin layer drying of paddy. In another study, ReLU function was used in the hidden layers for paddy dried in a continuous dyer (Jin, Wong, et al., 2021).

2.4.3 Optimizers

The optimization technique is responsible for minimizing the loss and achieving precise results. They change the values of attributes like weights and learning rate to reach the global minimum. Understanding their working can help to select the best optimizer for different types of problems. Some of which include Gradient descent, AdaGrad, RMSProp and Adam.

2.4.3.1 Gradient descent

Gradient Descent is the most popular method used to minimize the cost function. It iterates over the training examples to find the weight and bias values corresponding to the local minimum. By calculating the partial derivative, the function measures the change in the cost function with respect to change in the attributes. The size of the steps taken towards the local minimum depends on the learning rate. If the learning rate is too large it will keep on skipping the global minima. However, if the learning rate is too small, it will take a long time for the cost to converge to the minimum (Géron, 2019). The equation 2.5 are used to describe the gradient descent optimization (Ruder, 2016).

$$\theta = \theta - \eta \nabla_{\theta} \mathrm{J}(\theta) \tag{2.5}$$

Where, $\mathrm{J}(\theta)$ is the cost function and η is the learning rate, ∇_{θ} is the partial derivative of cost function, θ is the weight parameter.

There are 3 different approaches to achieve gradient descent algorithm (Bisong, 2019): the Stochastic Gradient Descent (SGD); the Batch gradient descent; and the Mini-batch gradient descent.

In SGD, cost for each training step is calculated followed by updating the parameters. These steps are repeated one by one for all the examples. Since only one example is used at a time the cost fluctuates but gradually decreases over time. The batch gradient descent method computes gradient over the entire training dataset set to move towards the global minimum. The mean value of the gradient calculated in one epoch is used to update the weights. Consequently, for large data this optimization process may take a long time. Mini-batch gradient descent randomly divides the training data set into batches of a specified size. The average cost over a batch is calculated, and the attributes are updated. this method attempts to combine the efficiency of batch gradient descent and fast computation of SGD (Bisong, 2019).

2.4.3.2 AdaGrad

The learning rate remains the same for gradient descent or even SGD with momentum. AdaGrad or Adaptive gradient was created by Duchi et al. (2011). Its main characteristics is that it updates the learning rate for every parameter at every epoch. The update rule for the AdaGrad algorithm is defined by equations 2.6 and 2.7 (Géron, 2019):

$$s = s + \nabla_{\theta} \mathrm{J}(\theta) \otimes \nabla_{\theta} \mathrm{J}(\theta) \tag{2.6}$$

$$\theta = \theta - \eta \nabla_{\theta} \mathrm{J}(\theta) \oslash \sqrt{s + \varepsilon} \tag{2.7}$$

The s term adds up the square of gradients. The ε in the denominator is the smoothening term and is added to avoid division by zero. ⊗ denotes element wise multiplication whereas ⊘ represents element wise division. If different parameter sets have no significant change in the result, the algorithm provides small updates. Alternatively, if the results of two parameter sets are significantly different, it sends large updates. This technique was proven to give improved results for sparse data (Lydia & Francis, 2019).

2.4.3.3 RMSProp

Root Mean Square Propagation was developed by Hinton et al. (2012) to overcome vanishing and exploding gradients in mini-batch back propagation. It uses the running average of square of gradients to adjust the learning rate after each epoch. The seed learning rate is usually 0.001 (Halgamuge et al., 2020). The equations below (2.8 and 2.9) define the RMSProp algorithm (Géron, 2019):

$$s = \beta s + (1 - \beta)\nabla_\theta \mathrm{J}(\theta) \otimes \nabla_\theta \mathrm{J}(\theta) \quad 2.8$$

$$\theta = \theta - \eta\nabla_\theta \mathrm{J}(\theta) \oslash \sqrt{s + \varepsilon} \quad 2.9$$

In these equations s is the square of the gradients and β is the decay rate with a default value of 0.9.

2.4.3.4 Adam

Adam stands for *Adaptive moment estimation*; it was developed by Kingma and Ba (2014) of the University of Amsterdam and Jimmy Ba of the University of Toronto. It combines the concepts of RMSProp and AdaGrad optimization, to produce better performance. This optimizer reduces the need to tune the learning rate. The optimization technique is given by the equations 2.10-2.14 (Géron, 2019).

$$m = \beta_1 m + (1 - \beta_1) \quad 2.10$$

$$s = \beta_2 s + (1 - \beta_2)\ \nabla_\theta \mathrm{J}(\theta) \otimes \nabla_\theta \mathrm{J}(\theta) \quad 2.11$$

In these equations *m* and s are the first and second moments, respectively. The first moment is the mean, and the second moment is the uncentered variance. The exponential decay for first and second moment is given by $\beta_1$and $\beta_{2,}$ respectively. In the equations t denotes the iteration number. The default value for β_1 is 0.999 and for β_2 is 0.999, while ε is initialised to a really small value of 10^{-8}.

$$\widehat{m} = \frac{m_t}{1 - {\beta_1}^t} \quad 2.12$$

$$\hat{s} = \frac{s}{1 - {\beta_2}^t} \quad 2.13$$

$$\theta = \theta + \ \eta\widehat{m} \oslash \sqrt{\hat{s} + \varepsilon} \quad 2.14$$

In several studies the Adam optimizer was found to converge the network with lowest loss values as compared to SGD, RMSprop and AdaGrad (Okewu et al., 2019; Saleem et al., 2020).

2.4.4 ANN model architectures

2.4.4.1 Feed forward network (FNN)

The feed forward neural network is the simplest form of ANN. Each network consists of two layers at least: the input and the output ones. Networks dedicated to more complex tasks require addition of one or more hidden layers. All layers are fully interconnected with the exception of nodes of the same layer. The three forms of layers in a feed forward neural network – input, hidden and output layers may perform specific tasks. The input layer introduces the data. The number of input nodes/neuron within this layer is equal to the number of object parameters being used to predict the output. The output layer contains signals which are the solution of performed task (Rabiej & Rabiej, 2021). The hidden layer connects the input and the output layers. Each connecting link carries a weight. Two operations take place in a neuron after it receives input from all the nodes in the previous layer. First, the dot product of the inputs and corresponding weights is carried out, then a bias term is added to the product. Afterwards, the result is passed to an activation function to produce the output (activation value) that would be past to the next layer (Equation 2.15 and Fig 2.3).

$$output = f\left(\sum(X_n W_n + bias\right) \qquad 2.15$$

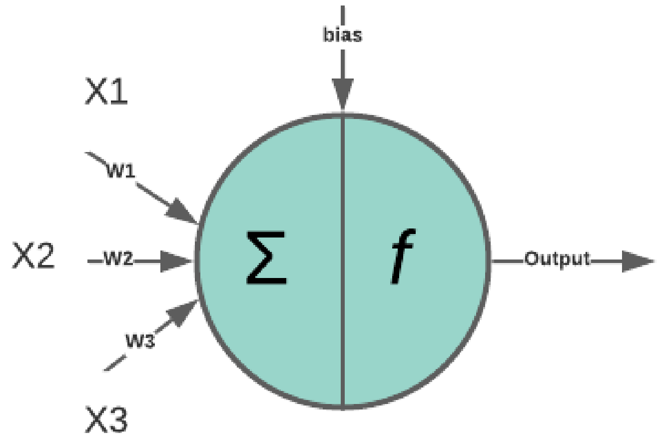


Figure 2.3 Working of a feed-forward neuron adapted from Goyal & Parashar (2018)

Many feed forward networks with varying number of layers and neurons have been proposed in the literature to approximate the relationship between drying variables. Islam et al., (2003) predicted the drying constants of the Page equation for hot air drying of potato using a 2 hidden layer FNN, with temperature, thickness of potato, relative humidity, and air velocity as the inputs. Similarly, numerous researchers forecasted parameters like moisture content and drying air speed for hazelnut (Ceylan & Aktaş, 2008); drying rate for turnip slices (Kaveh & Amiri Chayjan, 2017) and drying time of shelled corn in a microwave-fluidized dryer (Momenzadeh et al., 2011), to mention a few.

2.4.4.2 Recurrent neural network (RNN)

RNN is a particular class of ANN where the unit connections form a closed loop to feed the predicted output to the input layer for increased prediction precision. Thus, these networks are capable of incorporating all the available information within a defined time step. However, RNNs are difficult to train, incompetent to model long term dependencies and are susceptible to shrinking of gradients (Sutskever, 2013). Long-short term memory recurrent neural networks (LSTM) have been introduced by Hochreiter and Schmidhuber (1997) to overcome these issues, making them suitable for problems with long term dependencies and they have been used increasingly (Yu et al., 2019). In LSTM, three different gates (Equations 2.16-2.20) are used to control the information flow. They are, namely: the input gate (i_g), the forget gate (f_g) as well as the output gate (o_g) (Xie & Zhang, 2020). In these equations c is the cell state of the cell and $\tilde{c}$ is the candidate cell state used for calculating cell state. These gates help in selecting the apposite information for the network to keep or remove the information**.** The inner working of an LSTM cell is presented in in Fig. 2.4.

$$i_g = \sigma (W_i x_t + U_i h_{t-1} + b_i) \tag{2.16}$$

$$f_g = \sigma \left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{2.17}$$

$$o_g = \sigma (W_o x_t + U_o h_{t-1} + b_o) \tag{2.18}$$

$$\tilde{c} = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{2.19}$$

$$c = \sigma \left(f_g * c_{t-1} + i_g * \tilde{c}_t\right) \tag{2.20}$$

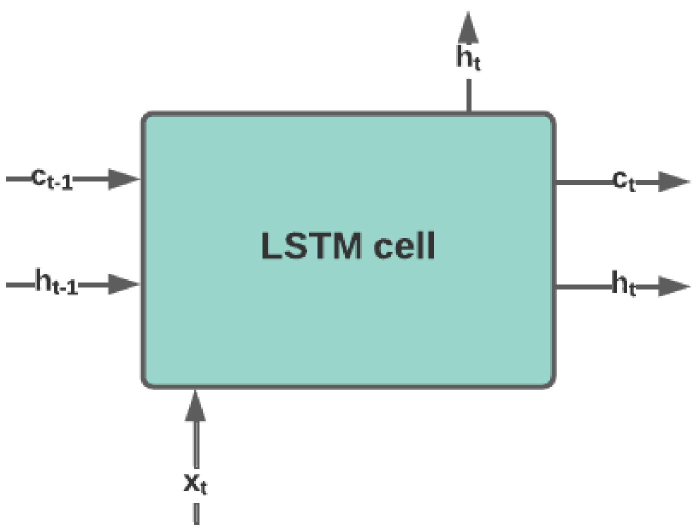


Figure 2.4 Working of an LSTM cell adapted from ElMoaqet et al. (2020)

Where, W represents the weights of the connections between inputs and hidden layers, U represents the recurrent connections in the LSTM cell. By default the LSTM cell uses sigmoid and hyperbolic tangent as the activation functions to make the computations. The cell state is the long-term memory of the network, whereas the hidden state is the memory of the previous cell which is passed to the next cell.

These cyclic networks have been used in drying technology to predict moisture content (Drăgoi et al., 2013; Torrecilla et al., 2005), one-step ahead water loss (Baruch et al., 2004) and water activity (Lertworasirikul & Tipsuwan, 2008).

2.4.5 Problems with artificial neural networks

Neural networks are proposed to solve non linear problems due to their depth. However, the stacking of layers in ANNs introduces the issue of vanishing and exploding of gradients. The backpropagation in a neural network for updating weights follows the chain rule of multiplication with partial derivatives (Grosse, 2017). Using the conventional activation functions such as sigmoid or hyperbolic tangent generates gradients that are either too small or too large. Multiplication of these small or large numbers can either kill the neuron or explode it, resulting in low prediction accuracy (Philipp et al., 2017). This problem impedes the convergence of the model, and the network is unable to minimize the error (Glorot & Bengio, 2010).

Fortunately, ReLU based FNNs are able to overcome this problem significantly for feed forward networks (Jain et al., 2020; Tan & Lim, 2019). Similarly, the use of LSTMs instead of plain recurrent networks are able to rectify the problem of vanishing and explosion of gradients.

Another challenge that could arise when training RNNs and even FNN is the problem of overfitting. During such scenario, the model performs well when present with the training data but performs poorly when it receives new data that it was trained on, such as the validation or test sets. Overfitting can be easily identified from the learning curve, the training loss would be on the decline, while the validation loss would be increasing. To address this issue, Prechelt (1998) introduced the technique of early stopping, in which training is terminated once the validation loss/metric stops improving for a certain number of epochs. The use of early stopping was substantiated by various researchers when working with feed forward networks (Ali et al., 2017; Lodwich et al., 2009; Mia et al., 2015) and LSTM networks (Bisht et al., 2020; Zhang et al., 2021).

FOREWORD TO CHAPTER III

This chapter reports the development of ANN models for microwave convective bed drying of cantaloupe. Feed-forward and dynamic models were investigated to predict the drying kinetics of cantaloupe. A number of values of hyperparameters were examined in this study to select the best configuration of the parameters. The models were developed to predict the moisture content and the product temperature.

CHAPTER III

STUDY OF TWO ANN APPROACHES FOR PREDICTING DRYING KINETICS OF CANTALOUPE IN A MICROWAVE CONVECTIVE DRYER

Abstract

The efficiency of two different modelling approaches for predicting moisture ratio and product temperature of cantaloupe slices in a microwave convective dryer were evaluated and compared. A Feed-forward Neural Network (FNN) and Long Short Term Memory Recurrent Network (LSTM) were used to develop neural network modelling. The input data set used included the drying time, air properties and radiation while the output was either moisture ratio or product temperature. A range of hyperparameters were then compared to find the best performing configuration. The obtained results indicated that the moisture ratio was predicted better than the product temperature. The R^2 was 0.997 and 0.955 for FNN and LSTM, respectively. The topology selected for FNN had 3 hidden layers with 64 neurons each and batch size of 32. The agreement between the experimental results and the theoretical model predictions was quite good based on the statistical criteria (the coefficient of determination [R^2] and mean squared error [MSE]). The data requirements for training an LSTM were also found to be high.

Keywords: cantaloupe, microwave-convective drying, LSTM, feed-forward

3.1 Introduction

Drying is an extensively used preservation technique to reduce postharvest losses (Mahayothee et al., 2019). Modelling of this process is critical to understand the behaviour of the material being dried and to optimize the drying conditions. A good model is beneficial for analyzing the various drying parameters which control the quality of the end product (Corrêa et al., 2011). Previous research works have used conceptual and mathematical models for predicting the drying kinetics of dried food products (Ceylan et al., 2007).

Recent studies have shown that ANN – a computational technique inspired from the human neurons – is capable of predicting and modelling non-linear and complex processes. The critical review of literature confirms the capability and importance of different ANN methods to solve a myriad of engineering problems. Chiang et. al (2004) applied static and dynamic ANNs to model the rainfall -runoff and predict heavy rainfall and thunderstorms in the future. Mahmoud et. al (2019) estimated the mechanical properties of sandstone using the simplest form of ANN i.e. Multi-layered perceptron, with a regression coefficient of 0.9816. In relation to drying, Ozsahin and Aydin (2014) used ANN to forecast the optimal drying temperature for two wood species and the bonding material.

For food drying in particular, several researchers have predicted the drying parameters of agricultural products like tomato (Movagharnejad & Nikzad, 2007), onion (Jafari et al., 2016), strawberry (Menlik et al., 2009) and apple slices (Polat & Kirmaci, 2012) using ANNs. A wide range of input variables and combinations of hidden layers and neurons have been explored to achieve high prediction accuracy. Singh and Kumar (2011) tested various architectures of FNNs for hot-air drying of sweet potatoes. They reported an R^2 of 0.9987 for the configuration of 2 hidden layers with 8 neurons in the first layer and 4 in the second hidden layer. Taghinezhad et. al

(2020) modelled the microwave-convective drying of quince with a neural network of 3 hidden layers and varying number of neurons per layer. Extensive investigations of applications of ANNs in Drying technology have been reported by (Aghbashlo et al., 2015; Sun et al., 2019).

However, no research was reported for studying the application of ANN for estimating the drying properties of cantaloupe. Moreover, investigations are needed to determine the applicability and effectiveness of different neural networks in light of available input–output patterns and quantitative characteristics of data sets.

This research capitalized on the use of ANNs in modelling the microwave convective drying process for cantaloupe. Specifically, the study has the following objectives: (1) To find out the best configuration for predicting the moisture ratio and product temperature using Feed-Forward Networks (FNN)and Long Short Term Memory Recurrent Networks (LSTM). (2) To compare the performance of both of these methods with each other to model the microwave-convective drying process. (3) To determine the minimum data size required to train both models, without compromising the prediction accuracy.

3.2 Materials and Methods

3.2.1 Database preparation

The study incorporated data obtained from the experiment of microwave-assisted convective drying of cantaloupe slices, performed by Garcia, F.A. (Garcia, Fabiola et al. 2019). The materials and methods of the work are briefly mentioned as follows. The operating variables for the experimental work were three levels of the drying air temperature and the initial microwave power density (IMPD), ranging from 45 - 65℃ and 0 – 2 W/g, respectively (Table 3.1). A total of 13 runs were performed for each factorial combination with the central point (55℃+ 1W/g) requiring multiple runs. The dryer was run until the product reached a final moisture content of 15% (wb) or 17.65% (db). Throughout the drying experiment, the Data Acquisition System (DAQ) recorded the values of time, reflected power, incident power, ambient air temperature, product mass, product temperature, temperature of air entering and of the air leaving the drying system. All the captured parameters would serve as input parameters for training the FNN and LSTM.

Table 3.1 Experiment statistical design

Factors / Levels	Temperature (°C)	Initial Microwave power density (W/g)
1	45	0
2	55	1
3	65	2

To ensure that the dataset is consistent and that the network can train properly, the duplicate values were removed from the dataset. The Savitzky – Golay smoothening was performed using the software Curve Expert Professional ver. 2.6.5 (Daniel G. Hyams, USA). The smoothener was used to remove the absurd values of the product mass which might be captured due to interfering signals of the sensors in the DAQ. The moisture ratio (MR) of the cantaloupe slices during the drying experiments was calculated using the following equation:

$$MR = \frac{M - M_e}{M_o - M_e} \tag{3.1}$$

Where M is the moisture content (dry basis) at any time t, M_o is the initial moisture content, M_e is the equilibrium moisture content. The M_e was assumed to be zero for microwave drying.

3.2.2 Data preprocessing

The prepared database was then preprocessed separately for feeding to FNNs and LSTMs in such a way that the particular ANN model understands it. The input parameters for predicting product temperature and moisture ratio are given in Table 3.2.

Table 3.2 Input parameters

Output Parameter	**Input Parameter**
Moisture Ratio	Time, Product Temperature, Reflected Power, Incident Power, Ambient Air Temperature, Exit Air temperature, Entering Air Temperature
Product Temperature	Time, Reflected Power, Incident Power, Ambient Air Temperature, Exit Air temperature, Entering Air Temperature

3.2.2.1 Feed-forward neural network

To ensure the data is well represented across the training, validation and test sets, the data was first grouped into 5 bins using the dry-basis moisture content. Afterwards the 6600 training examples were shuffled, and split to the training, validation, and test sets, using a split ratio of 70%, 15% and 15%, respectively. This data split ratio was selected on the basis of preliminary trails such that a model can fit to the training data perfectly and be able to generalize well to new data. Moreover, enough data for the validation test was needed to prevent overfitting. Therefore, balance between enough data for training and validation was achieved with the given split ratio. The generalization error was measured on the 15% test set.

The training set was normalized using eq. 3.2. The standardized data had a mean of 0 and a standard deviation of 1.

$$z_i = \frac{x_i - \mu}{\sigma} \tag{3.2}$$

Where, z_i is i^{th} the normalized value, x_i is the i^{th} value, μ is the mean and σ is the standard deviation.

3.2.2.2 Long short term memory recurrent networks

A training, validation, and test pair for an LSTM consisted of the input parameters and the first fifty predicted values of the output parameter. Since the sequence of data plays a crucial role, the data was not shuffled when training the LSTM. The training set was normalized between 0 and 1 using the Minmax scaler from ScKit learn preprocessing module. The training, validation and test set were produced using a split ratio of 70%, 15% and 15%, respectively.

3.2.3 ANN model construction

This research was done with Python using the TensorFlow library and Keras API, developed by Google. The number of input neurons were kept equal to the number of parameters used for training the networks. For fine-tuning the networks various combinations of the following hyperparameters – number of hidden layers, number of nodes per hidden layer, batch size, were used. The levels of each hyperparameter are presented in the Table 3.3.

Table 3.3 Experimental factorial design of neural network

Hyperparameter	Levels
Number of hidden layers	1, 2, 3
Number of neurons per hidden layer	4, 16, 32, 64
Batch Size	16, 32, 64

The Adam optimization algorithm was used for backpropagation and the learning rate was set to 0.001. The ReLu function given by Equation 3.3 was used as the activation function for hidden layers. The model with the highest coefficient of determination and lowest mean squared error was chosen as the best network.

$$f(x) = \max(x, 0) \quad 3.3$$

Pearson's correlation coefficient (r) given by Equation 3.4 was used to select the best input parameter for predicting moisture ratio and product temperature. Using this coefficient as a guide was more realistic than experimenting with numerous network designs obtained from a full factorial design of all the input parameters. The uncorrelated parameters with the output were removed to identify if the accuracy of network improves further.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad 3.4$$

Where, x_i are the values of x-variable in a sample, $\bar{x}$ is mean of the values of the x-variable, y_i are the values of y-variable in a sample and $\bar{y}$ is the mean of the values of the y-variable.

3.2.4 Model evaluation

To evaluate the performance of the model on data that wasn't exposed to it during training, the model was evaluated using mean square error, the mean absolute error, and the coefficient of deamination.

3.2.4.1 Mean squared error

Mean Squared Error (MSE) was used after each iteration, to monitor the loss between the actual/experimental and the corresponding predicted value. MSE is given by the following equation:

$$MSE = \frac{1}{n}\sum_{i=0}^{n}\left(Y_i - \hat{Y}_i\right)^2 \quad 3.5$$

Where, Y_i is the experimental i^{th} value, $\hat{Y}_i$ is the predicted i^{th} value and n is the number of data points Since, it calculates the square of the error, the contribution of large errors is more pronounced than the smaller ones. Hence, it directs the model to emphasize larger errors thereby acting as a suitable metric to minimize error with increasing number of epochs.

3.2.4.2 Mean absolute error

Mean Absolute Error (MAE) measures the average difference between actual and predicted values over the entire dataset. It is calculated using the following equation:

$$MAE = \frac{1}{n}\sum_{i=0}^{n}\left|\left(Y_i - \hat{Y}_i\right)\right| \tag{3.6}$$

Where, Y_i is the experimental i^{th} value, $\widehat{Y}_i$ is the predicted i^{th} value, and n is the number of data points.

3.2.4.3 Coefficient of determination

Coefficient of Determination (R^2) can be interpreted as the proportion of data points correctly predicted. The output lies between 0 and 1, with 1 being the ideal value which means that the model fits with every point of the data perfectly. It is calculated by the eq 3.7.

$$R^2 = \left(\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}\right)^2 \tag{3.7}$$

Where, x_i are the observed values in a sample, $\bar{x}$ is mean of the values of the x-variable, y_i are the predicted values of a sample and, $\bar{y}$ is the mean of the values of the y-variable.

3.2.5 Determination of minimum size of data

The previous objectives were achieved using training examples (input parameters) captured at an interval of 30 seconds. However, to determine the minimum size of data needed to train either the

FNN or LSTM, both type of networks was trained using data that was captured and recorded at increasing time intervals. The R^2 value was compared for the different time intervals.

3.3 Results and Discussion

3.3.1 ANN architecture selection

The FNN and LSTM with different configurations of hidden layers, number of neurons per hidden layer and batch size were applied for predicting both moisture ratio and product temperature.

The FNN with 3 hidden layers, 64 neurons in each hidden layer and a batch size of 32 appeared to be the best selection due to the lowest MSE and highest R^2. The selected FNN had an R^2 of 0.9994 and 0.9948 for training and validation sets, respectively. Similarly, the best LSTM had one hidden layer, 16 neurons per layer, and a batch size of 32 training examples. The LSTM gave an R^2 of 0.9717 and 0.9558 for training and validation sets, respectively. The evaluation results for both networks are shown in Table 3.4.

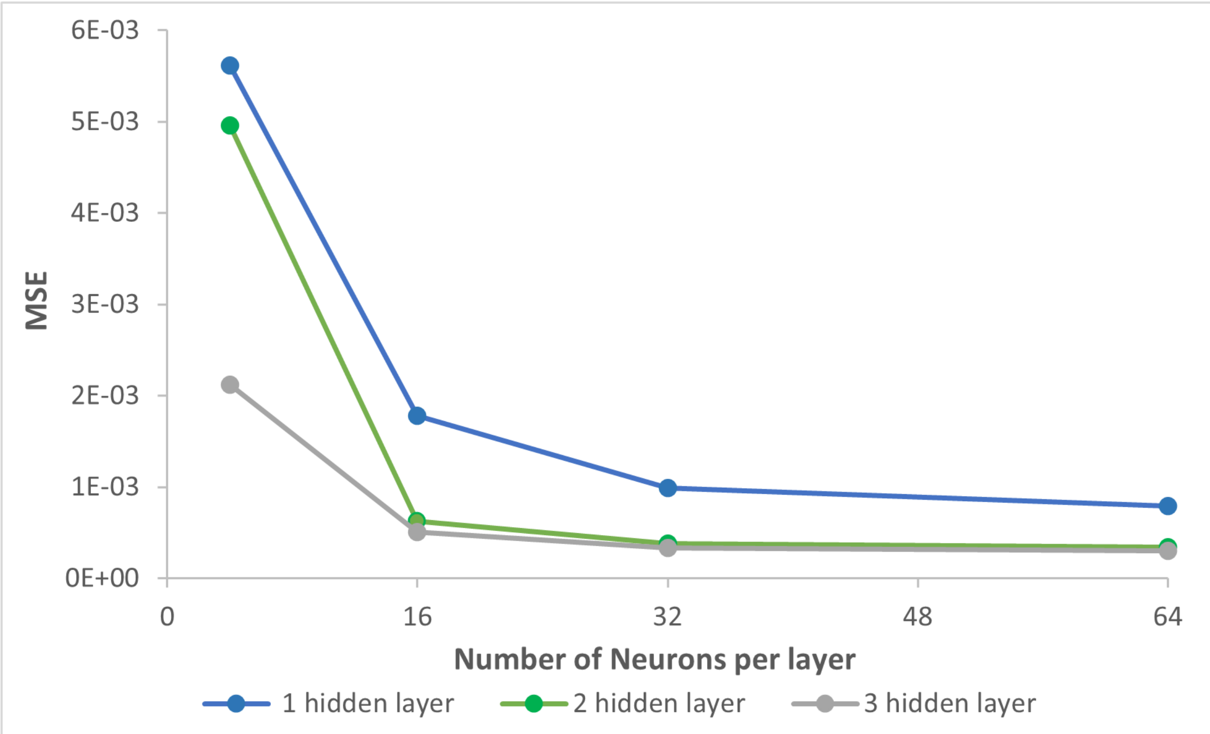
From Table 3.4(a), it is certain that the ability of selected feed-forward network to predict moisture ratio was superior to that for predicting the product temperature, due to higher value of R^2 for moisture ratio. The same was true for the chosen recurrent model. However, it was noticed that the feed-forward network slightly outperformed the recurrent network in predicting the moisture ratio and product temperature. The FNN resulted in lower MSE and higher R^2 for both drying parameters. Furthermore, the results were in contrast with the study conducted on thyme leaves drying where recurrent networks were found to predict moisture ratio with more precision (Adabi et al., 2013). Another research experiment for microwave-hot air drying of mushroom revealed that RNNs had better accuracy than FNN for forecasting moisture content (Omari et al., 2018).

Figures 3.1 and 3.2 show the variation of loss metric versus number of neurons per hidden layer for different number of hidden layers. It is evident from Figure 3.1 that complex networks with more hidden layers and neurons performed better for FNN. Whereas, in the case of LSTM, as the number of hidden layers and neurons increased, or the network became complex the MSE error started to decrease (Figure 3.2). In a similar study, a feed-forward network, and recurrent models with 30 neurons and tanh activation function were used to estimate moisture ratio where the recurrent model had higher accuracy (Nazghelichi et al., 2011).

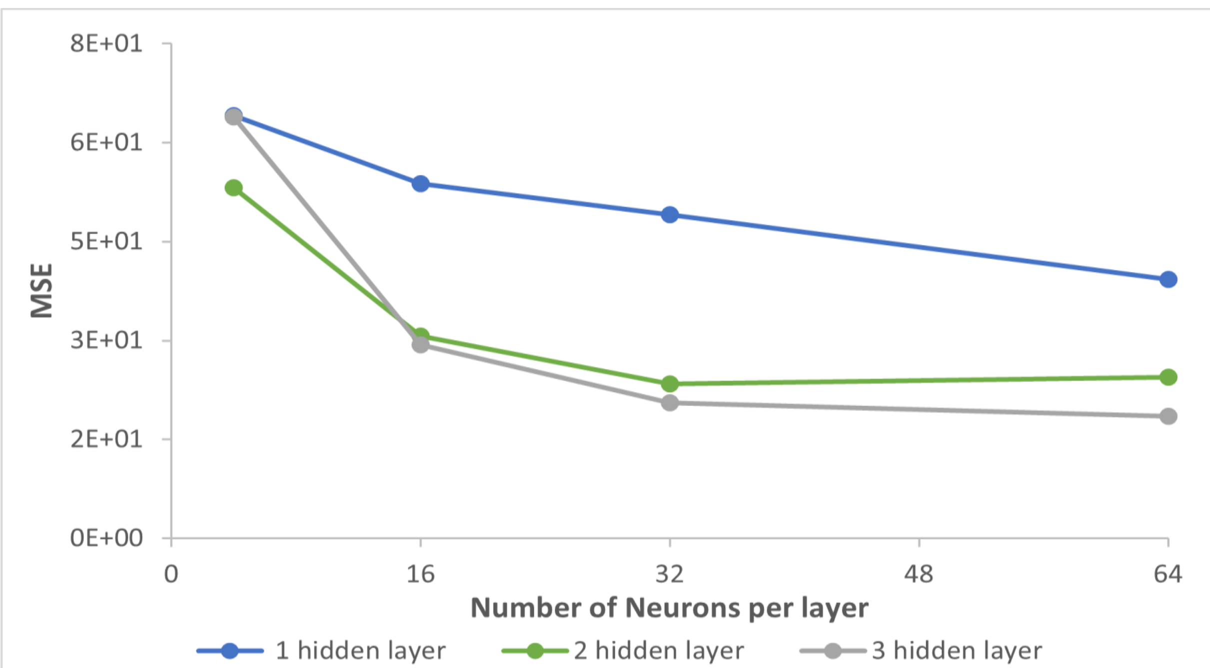
Figures 3.3 and Figure 3.4 represent the training and validation learning curves for the FNN and LSTM. From the graphs, it is clear that the networks neither overfits nor underfits, as the MSE decreases with increasing number of epochs. The plot for the training loss is an indicator of the well-fitted learning process whereas plots for the validation set signifies the good generalization capability of the network.

Table 3.4 Performance of the selected topology of (a) FNN and (b) LSTM models to predict each of the output parameters

Parameter	**Number of Nodes**	**Number of Hidden layers**	**Batch size**	**MSE**	**MAE**	**R^2**	**Epochs run**
(a)							
Moisture ratio	64	3	32	3.06E-04	7.93E-03	0.9947	632
Product Temperature	64	3	32	24.768	4.236	0.8504	619
(b)							
Moisture ratio	16	1	32	3.30E-03	2.96E-02	0.9537	136
Product Temperature	16	1	32	24.007	4.708	0.6652	64

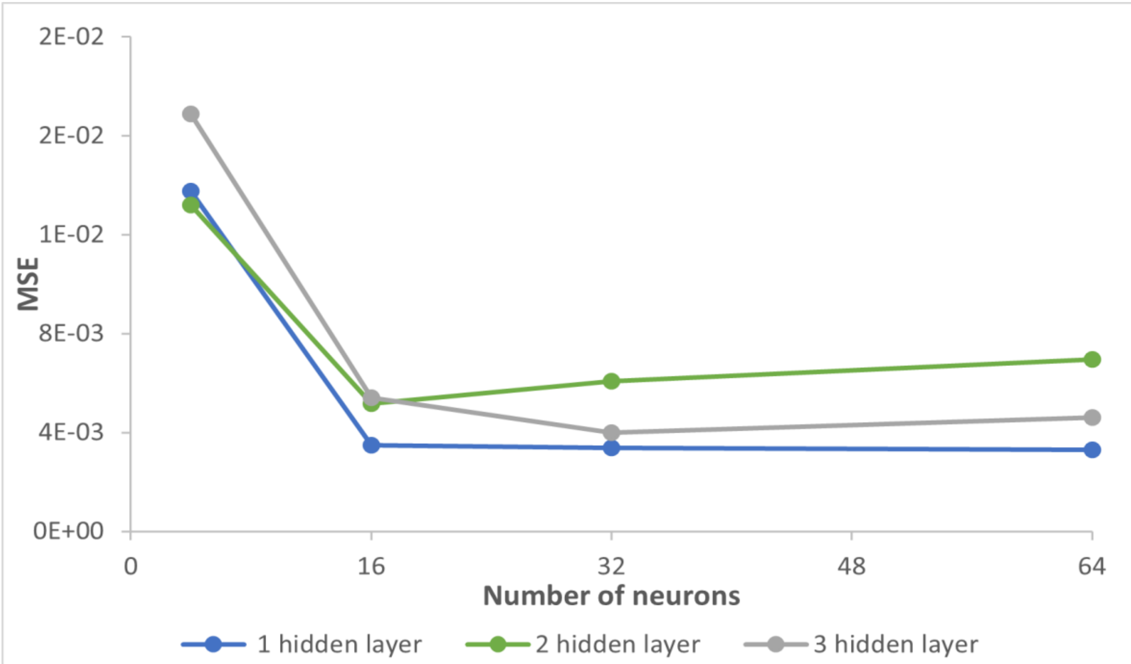


(a)

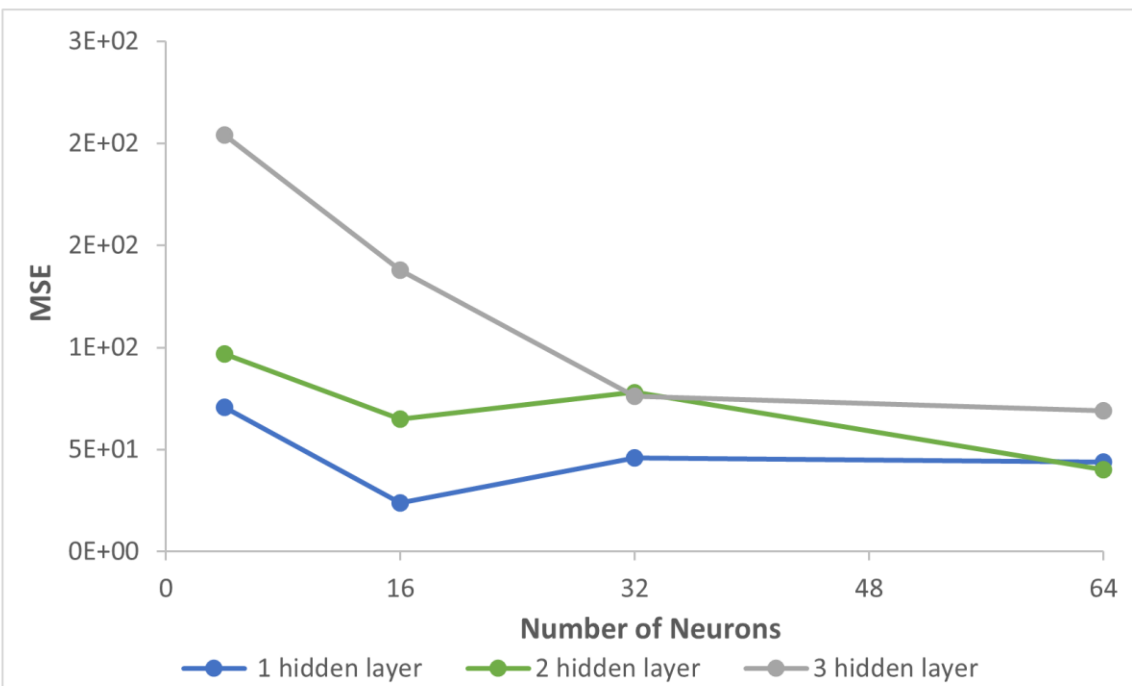


(b)

Figure 3.1 Mean squared error for different configurations of FNN in training phase for predicting (a) moisture ratio and (b) product temperature

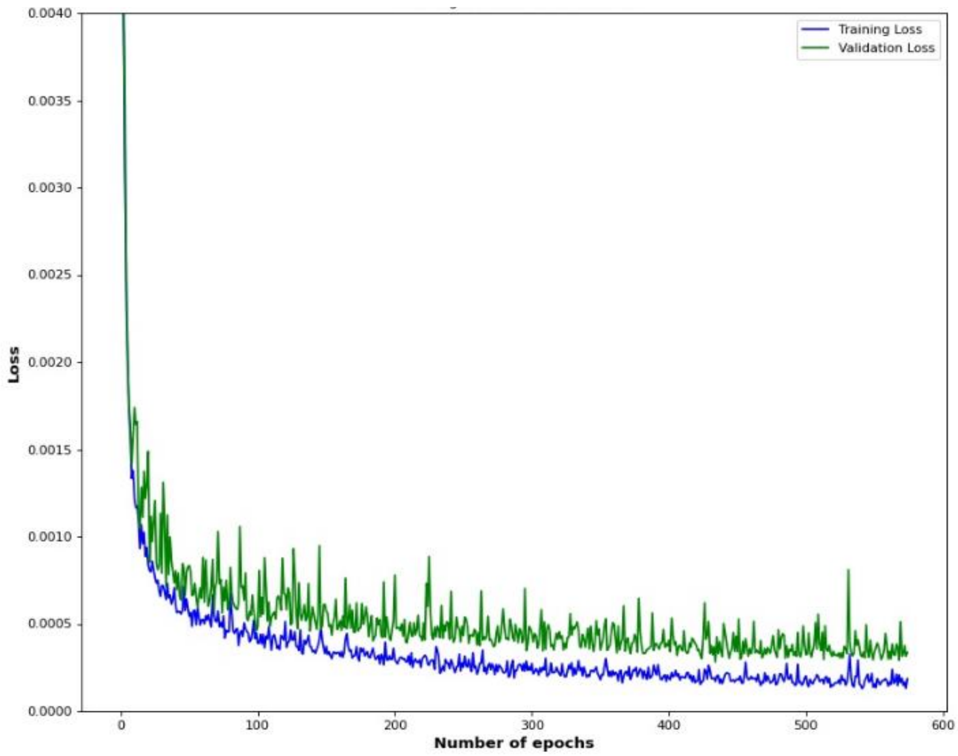


(a)

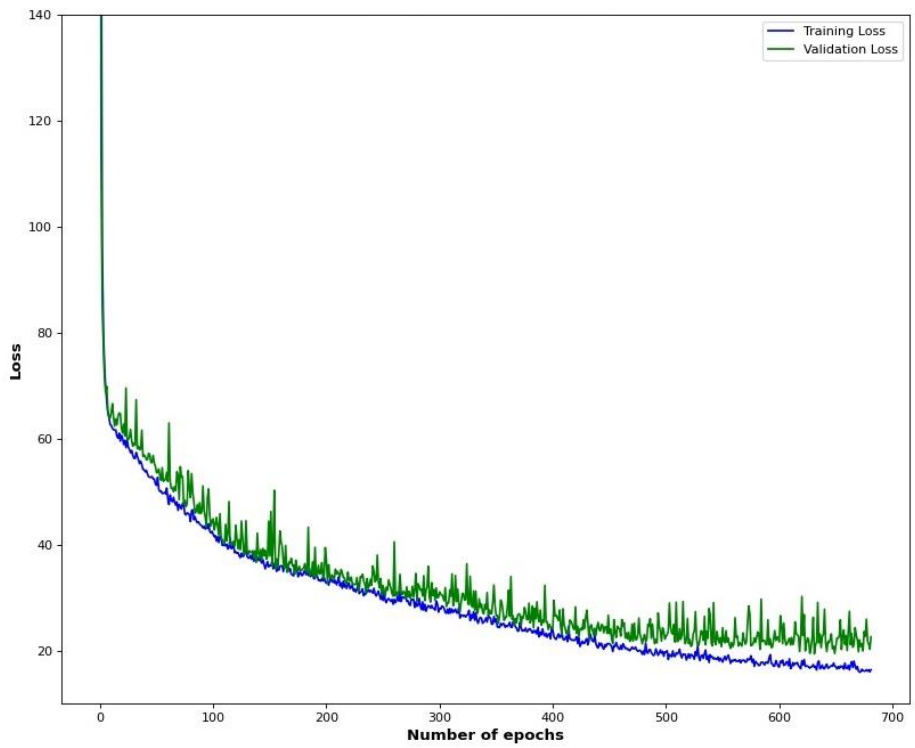


(b)

Figure 3.2 Mean squared error for different configurations of LSTM in training phase for predicting (a) moisture ratio and (b) product temperature

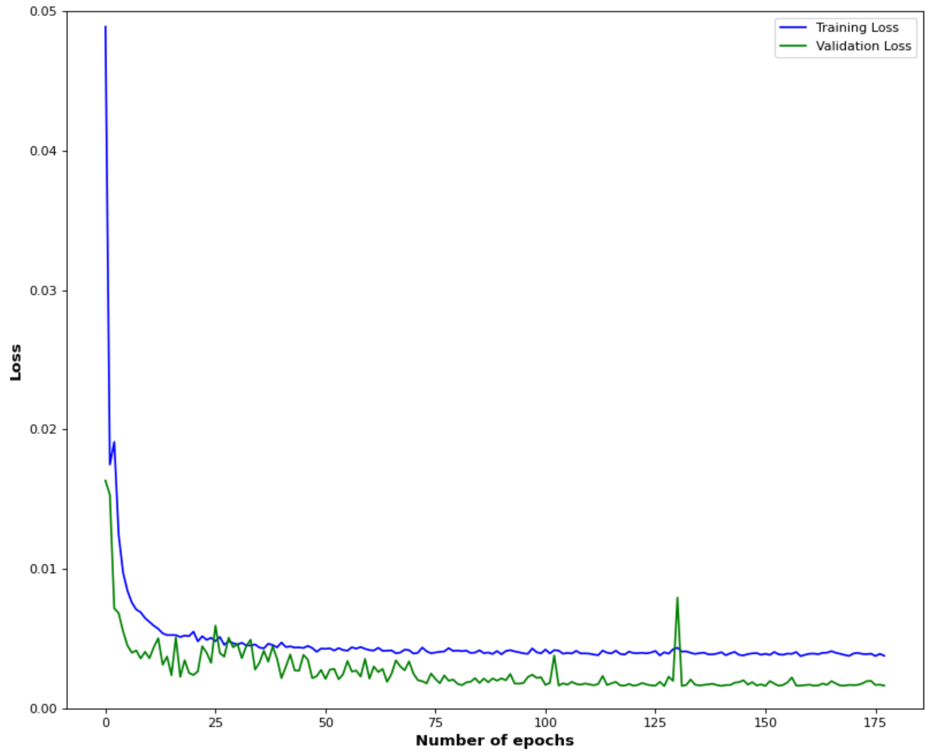


(a)

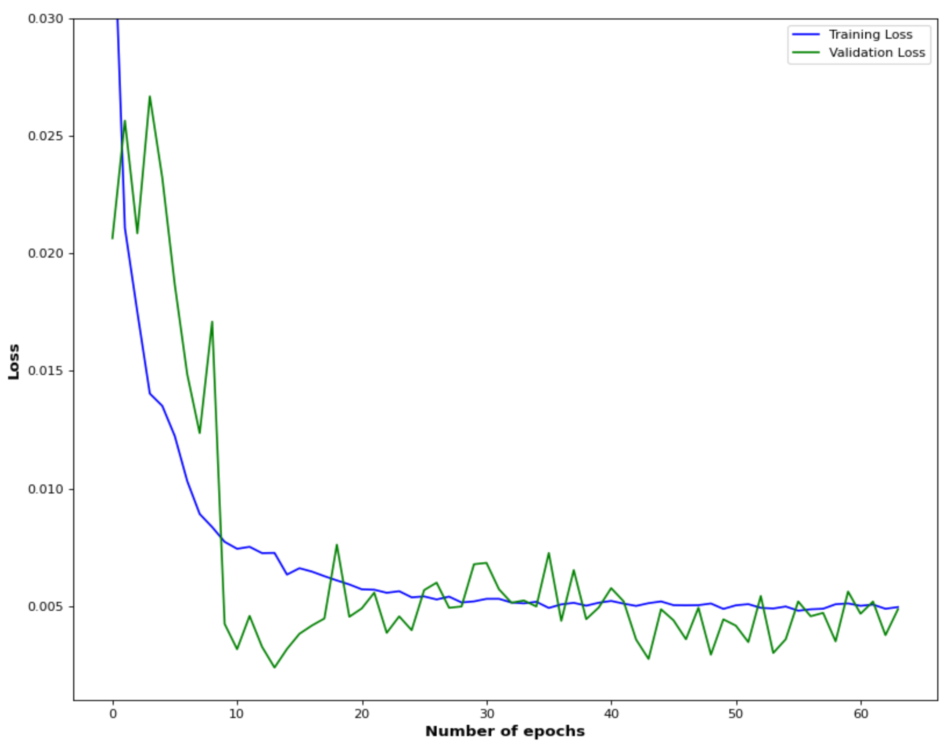


(b)

Figure 3.3. Learning curves of FNN to predict (a) Moisture ratio and (b) Product temperature



(a)



(b)

Figure 3.4 Learning curves of LSTM to predict (a) Moisture ratio and (b) Product temperature

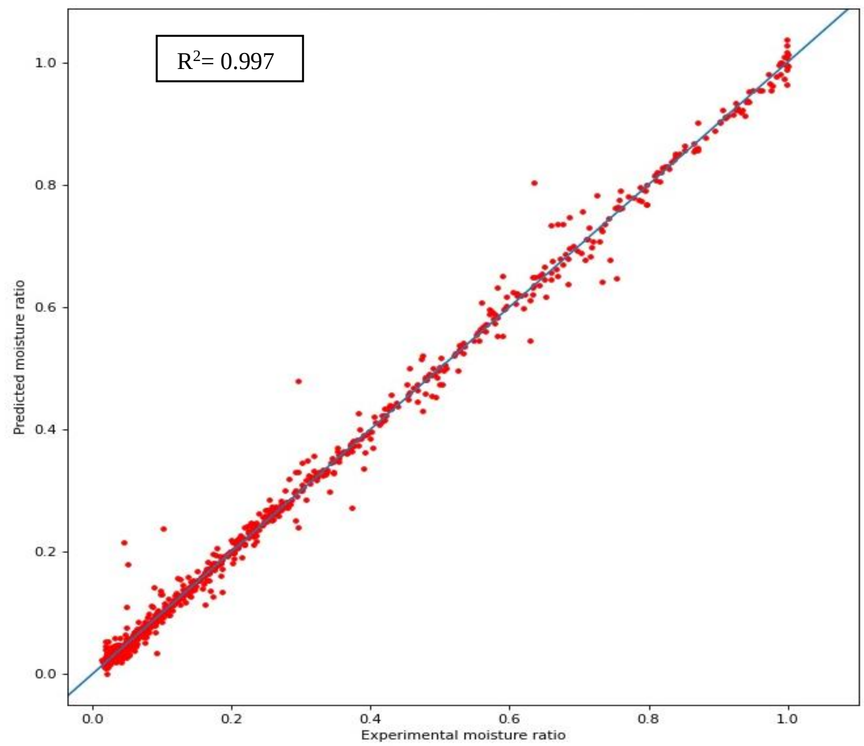
3.3.2 Model input selection

The Pearson's correlation coefficient was used to eliminate the input parameters that had negligible influence on the output parameter. The final selected model inputs and evaluation results for the trained model are given in Table 3.5. It was found that with the removal of reflected power and incident power that had low correlation coefficient, the network generalized better.

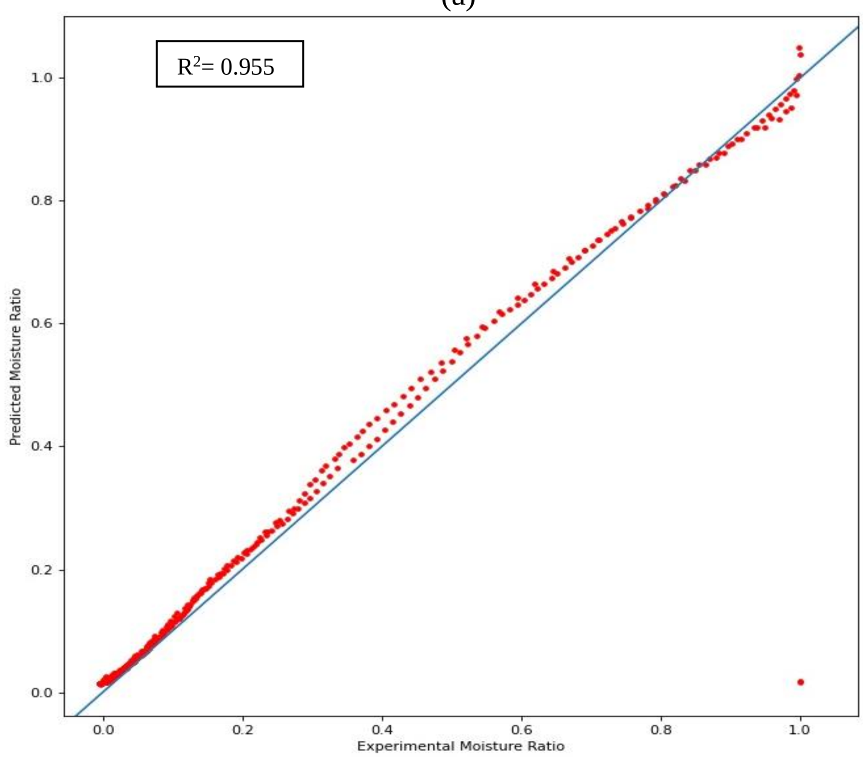
Table 3.5 Selected inputs and performance of networks for (a) FNN and (b) LSTM

Inputs	**Outputs**	**MSE**	**MAE**	**R^2**
(a)				
Time, Product temperature, Ambient air Temperature, Exit air temperature, Air in temperature	Moisture ratio	1.886E-04	7.612E-03	0.997
Time, Ambient air Temperature, Exit air temperature, Air in temperature	Product Temperature	19.768	3.046	0.861
(b)				
Time, Product temperature, Ambient air Temperature, Exit air temperature, Air in temperature, Moisture ratio	Moisture ratio	3.174E-03	1.411E-02	0.955
Time, Ambient air Temperature, Exit air temperature, Air in temperature, Product temperature	Product Temperature	22.196	3.862	0.758

Figures 3.5 and 3.6 compares the predicted values with the experimental output values of moisture ratio and product temperature for kinetic analysis of microwave convective drying of cantaloupe slices using the FNN and LSTM, respectively. It is clear from the graphs that both networks predicted moisture ratio better than product temperature since most of the predicted values are concentrated around the 45-degree straight line of observed values. The schematic structure of the feed-forward and recurrent model is shown in Figure 3.7. The key difference between these models was that in the recurrent network a feed back loop was present. This loop feeds the output of the current state, Δt, as one of the inputs for the next step.

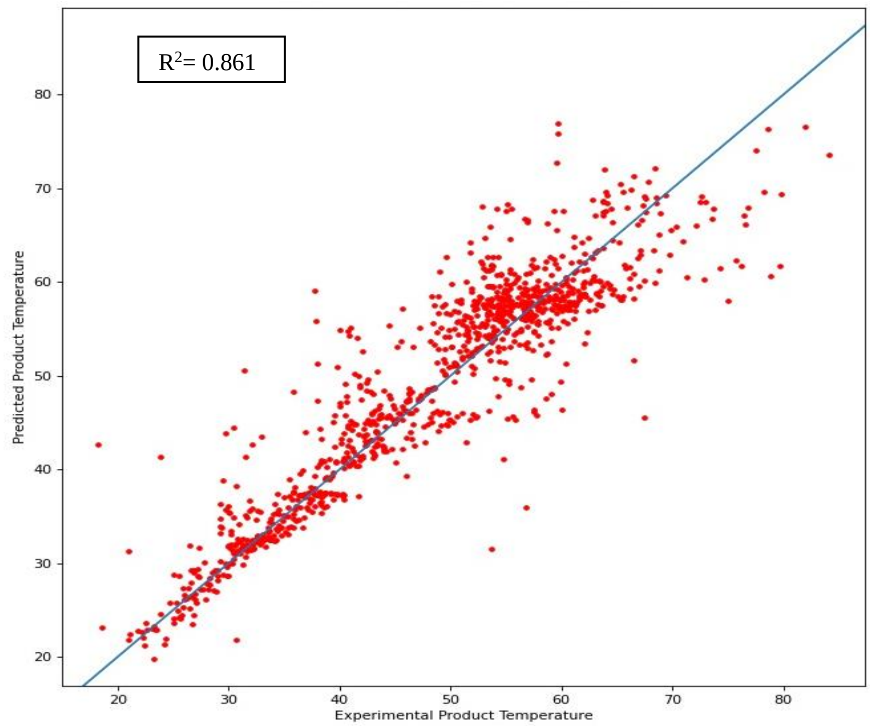


(a)

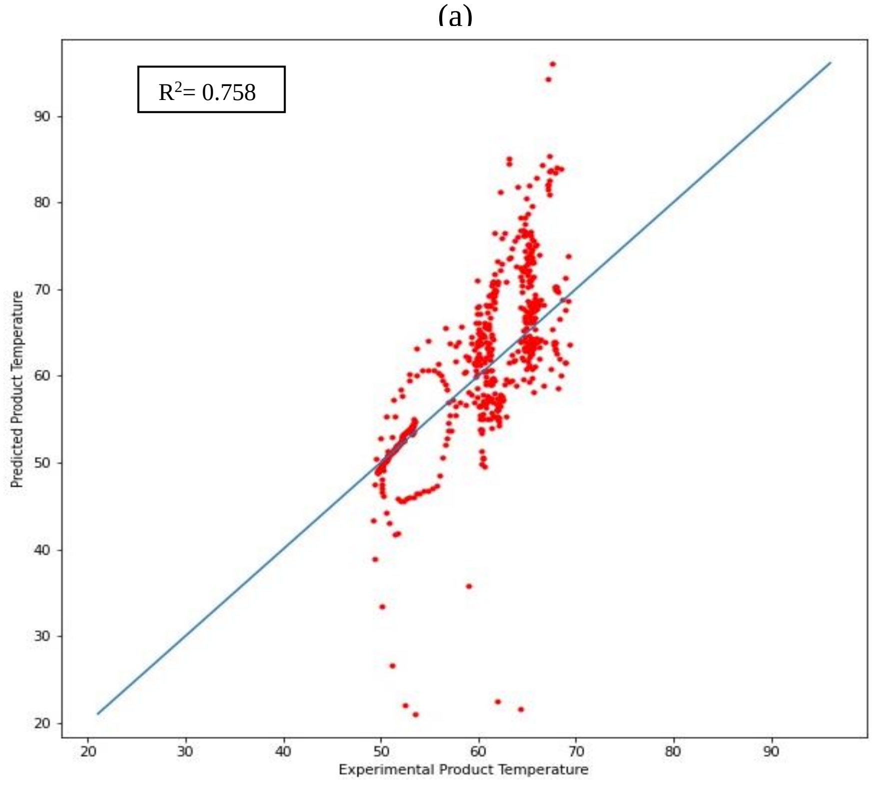


(b)

Figure 3.5 Comparison of predicted and experimental values for moisture ratio prediction using the final selected (a) FNN and (b) LSTM for the test set

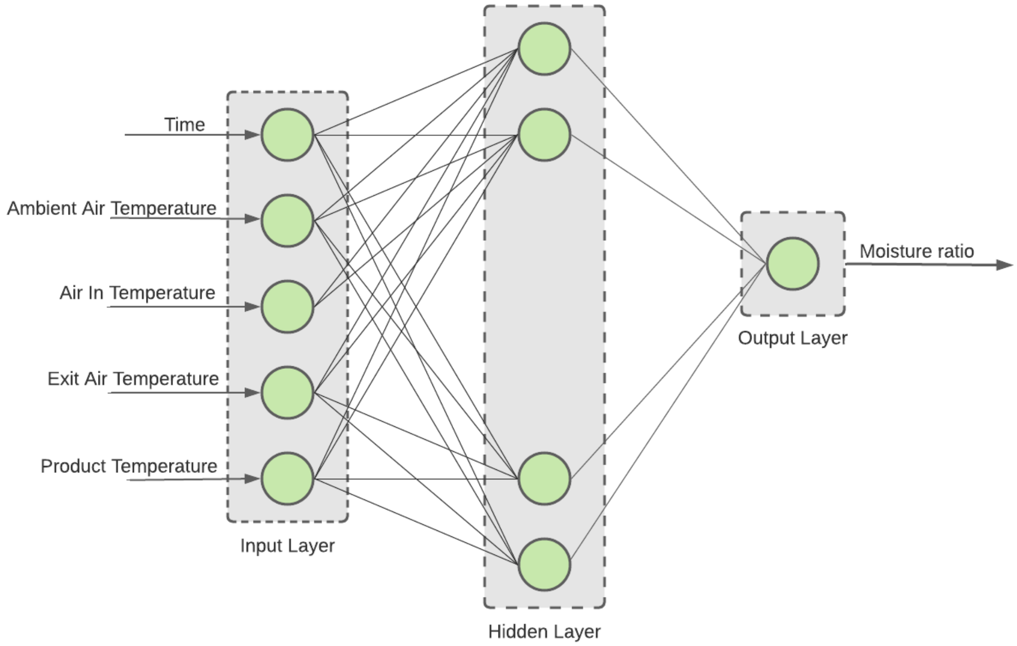


(a)

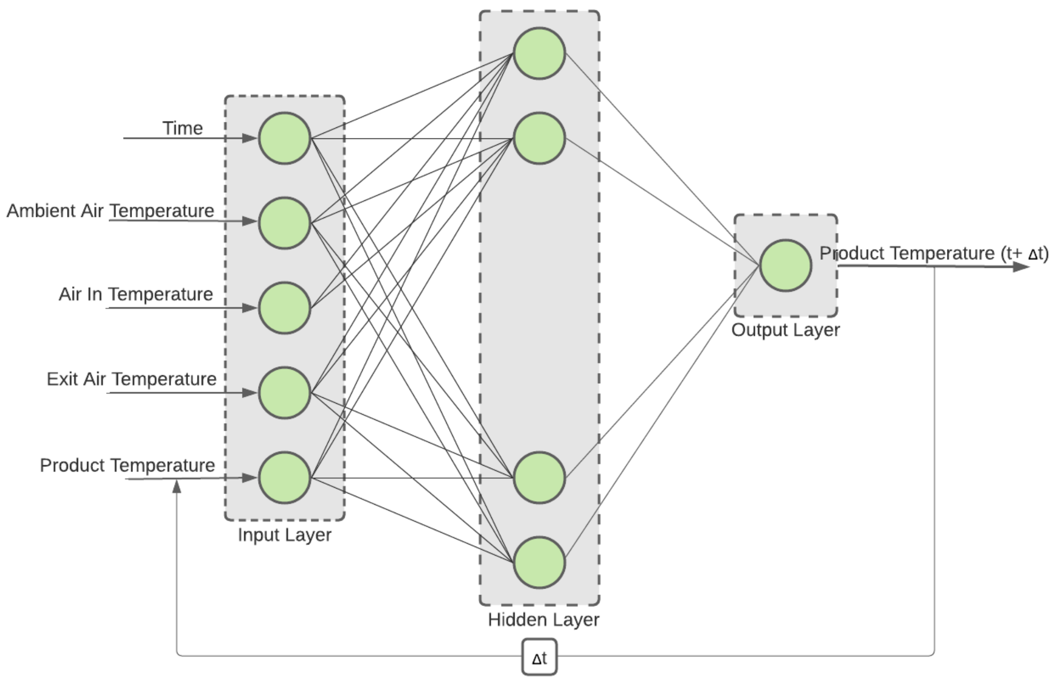


(b)

Figure 3.6 Comparison of predicted and desired output values for product temperature prediction using (a) FNN and (b) LSTM for the test set



(a)



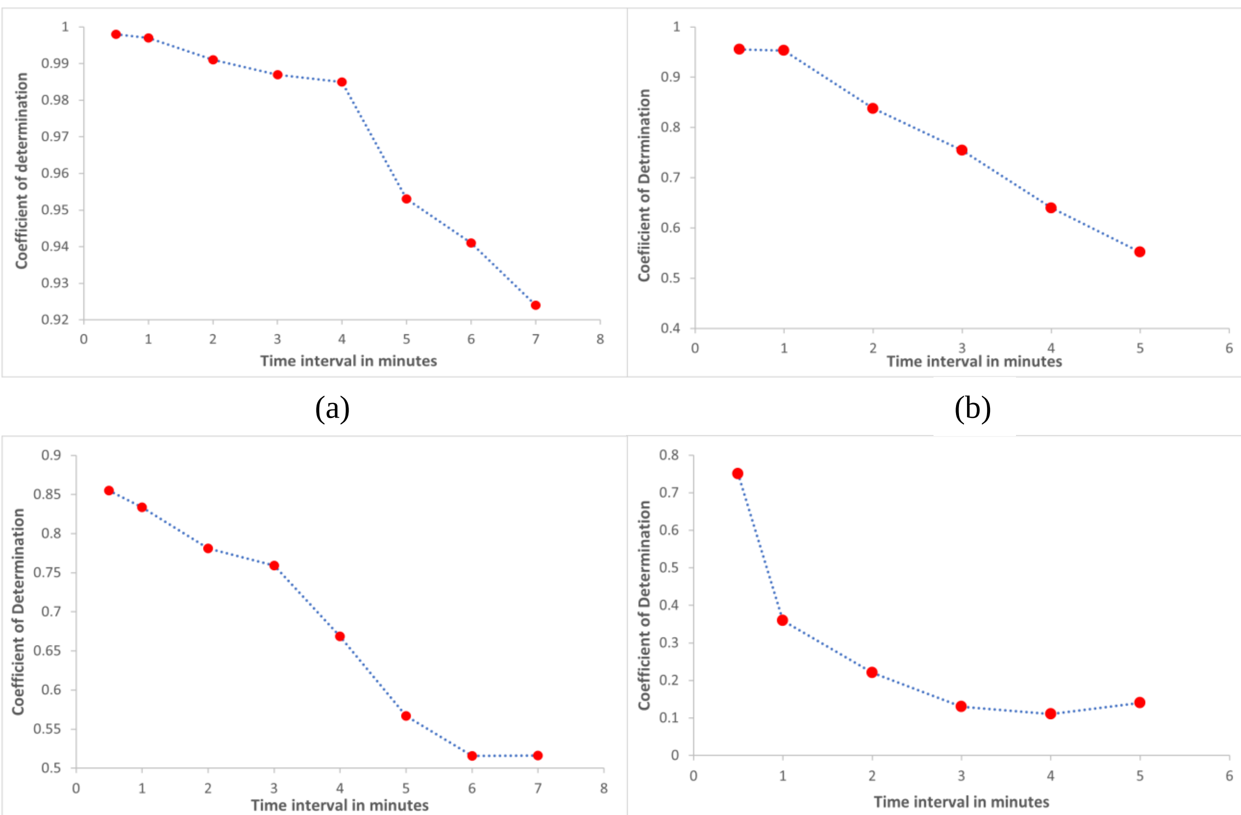
(b)

Figure 3.7 Schematic structure for (a) FNN predicting moisture ratio and (b) LSTM predicting product temperature

3.3.3 Minimum training data

The networks developed in objective 1 were trained using training examples (input parameters) captured at an interval of 30 seconds. However, in objective 3, the goal was to determine the minimum size of training data needed to obtain acceptable model performance. To achieve this goal, a series of FNN and LSTM models were developed using training examples captured at different time intervals, ranging from thirty seconds to seven minutes.

To determine the minimum data size, the coefficient of determination (R^2) for each model was plotted against the sampling interval. For moisture ratio prediction, the FNN had a significant drop in the R^2 above 4 minutes sampling interval (Fig 3.8(a)).



(a) (b)

(c) (d)

Figure 3.8 Variation of coefficient of determination with time interval for moisture ratio predicted by (a) FNN and (b) LSTM; and for predicting product temperature by (c) FNN and (d) LSTM

However, for a recurrent network, a steep drop was observed when the time interval was increased to more than 2 minutes (Fig 3.8(b)). Similarly, for predicting product temperature, the performance of the FNN decreased significantly after 3 minutes. Whereas, the R^2 for the LSTM dropped immediately after increasing the interval to 1 minute (Fig 3.8(c,d)). Hence, it was concluded that the feed-forward model was able to create highly sufficient predictive capability even at 3 minute sampling interval.

3.4 Conclusion

This work used feed-forward and recurrent neural networks to assess the drying kinetics of microwave convective drying of cantaloupe slices. Various number of hidden layers, number of neurons per hidden layer and batch size were experimented. The trained FNN models were found to attain higher prediction accuracy than the dynamic LSTM models. It was also found that both the ANN models gave a better prediction of moisture ratio than the product temperature. Moreover, it was found that LSTM needed more data to improve its prediction capability, however such improvement requires more computational resources. The schematic structure selected in the study had 3 hidden layers with 64 neurons per layer and was trained using a batch size of 32. This topology was able to predict moisture ratio with MSE = 0.00018 and R^2 =0.997. This study has shown that for an FNN the training data can be captured at 4-minute intervals which has around 600 data points and still achieve acceptable results (with R^2 for test set above 0.985). The methodology in this paper could be applied to other products as well.

FOREWORD TO CHAPTER IV

In Chapter III, ANN models were developed for microwave convective bed drying of cantaloupe. The best performing ANN model obtained from Chapter III was compared with drying models to predict the moisture ratio of a new experiment of drying of cantaloupe. Further, experiments to analyze the quality of the dried product were performed.

CHAPTER IV

COMPARATIVE STUDY OF MATHEMATICAL AND ANN MODELLING FOR MICROWAVE CONVECTIVE DRYING OF CANTALOUPE

Abstract

The drying of cantaloupe slices in a microwave assisted convective dryer was investigated. The drying conditions such as inlet air temperature and initial microwave power density were varied. Different mathematical models and an ANN model were fitted to the drying data. The models were compared using statistical parameters such as coefficient of determination and standard error. The change in colour, Hue and chroma were calculated for each drying trial. The results showed that the Two-term model was best among the mathematical models in predicting the moisture ratio. In the case of ANN, the results were comparable with the two-term model. Further, the physical and nutritional quality parameters of the dried product were also studied.

Keywords: cantaloupe, moisture ratio, ANN, phenolic content, antioxidant activity

4.1 Introduction

Food security has been a growing concern around the world for several decades. More than two billion people around the world suffer from a lack of access to food that is both safe and nutritious (FAO, 2020). Furthermore, the situation appears to have deteriorated in the wake of COVID 19, which has impacted the global food supply chain in a negative way (Gundersen et al., 2021). According to a 2017 report by FAO, about 43% of the world's fruit and vegetables produced are being wasted (FAO, 2017). The environmental impact of food waste is also enormous due to high requirement of natural resources (Del Borghi et al., 2014). Thus, employing preservation techniques to minimize waste is critical for both social and economic benefits.

Fruits and vegetables are an important source of various bioactive compounds which offer anticarcinogenic and cardiovascular benefits. An excellent source of vitamin A and C which is also rich in potassium and carbohydrates is cantaloupe (USDA, 2019). Although, due to its high moisture content (Ghanbarian et al., 2008), it is highly susceptible to enzymatic reactions and growth of microorganisms (McCollum et al., 2013) which make it difficult to store it in fresh form. In recent times, the demand for dried fruits has increased being a healthier substitute to sugary snacks. Their year-round availability and easy transportation add to the numerous benefits (Chang et al., 2016; Keast et al., 2011).

Various drying techniques have been investigated to reduce the moisture content of cantaloupe products like spray drying (Solval et al., 2012), foam mat drying (Salahi et al., 2015) and osmotic dehydration (Martínez-Valencia et al., 2011). Yet, there was limited research on the drying of cantaloupe using the popular convective drying method. Moreover, since convective drying has inherent longer drying time, the thermal stress on the product is high. To get the best out of convective drying it is usually used in combination with the microwave energy (Sadeghi et al., 2013).

One of the important aspects of drying is the drying kinetics which is often used to describe the moisture removal in the product, essential for the quality control. Many researchers use semi-empirical models based on the Fick's second law of diffusion such as Page model, Henderson and Pabis model, Two-term model, Logarithmic model, to predict the moisture ratio (Onwude et al., 2016). Recently, machine learning techniques like Artificial neural networks are also being used increasingly to predict the drying behaviour. Many researchers have compared both modelling techniques and found that well trained ANN model can replace the traditional theoretical approach (Chakraborty et al., 2016; Chayjan et al., 2014).

Therefore, the objectives of this study were (1) To investigate the drying behavior of cantaloupe in a microwave convective dryer; (2) To validate predictive mathematical models and ANN model relating changes in moisture ratio as a function of time; and (3) To analyze the colour, phenolic content and antioxidant activity of the dried product.

4.2 Materials and Methods

4.2.1 Cantaloupe

Fresh cantaloupes at commercial maturity, imported from USA, were obtained from a local supermarket in Saint-Anne-de-Bellevue, QC, Canada. The product was stored at refrigerated temperatures of about 4 °C prior to its use. The fruit was peeled and sliced to a uniform size with a diameter of 23 mm and 6 mm thickness using a fruit and vegetable slicer (Nemco, USA). The moisture content of fresh cantaloupe was measured for each run by drying a sample of 5 g for 24h in a precision oven at 70℃ (AOAC, 1980).

4.2.2 Microwave convective dryer

The drying was done in a microwave-assisted dryer (Figure 4.1) at the post harvest technology lab at Macdonald Campus, McGill University, QC, Canada. The microwave generator was operating at 2450 MHz, with a maximum output power of 750 W. The product temperature was monitored using a fiber optic probe (Nortech Fibronic INC, model Canada). The mass of the samples, product and air temperatures, and microwave power were recorded at intervals of 30 s during convective microwave drying by a data acquisition and control unit (Agilent, model 34970A, USA). The three tuning screws were used to adjust and minimize the reflected power. The air blower with a heating element was connected to the bottom of the microwave cavity. It was used to maintain the desired air temperature during drying.

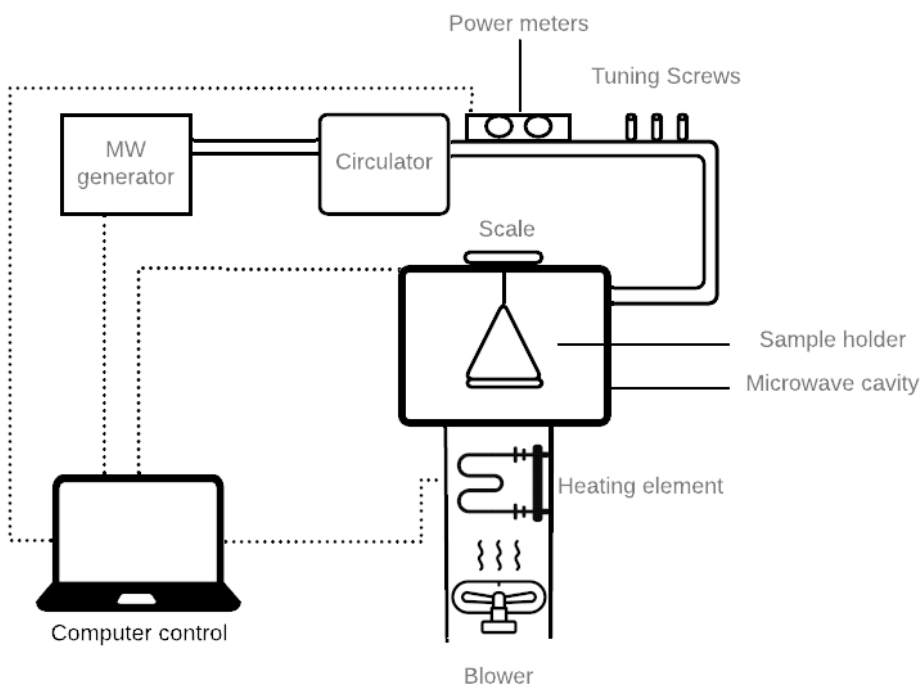


Figure 4.1 Schematic diagram of microwave-convective drying unit

4.2.3 Experimental procedure

The experiment was carried out by varying the air temperature and initial microwave power density (IMPD). The IMPD (W/g) was the applied microwave power at the start of the drying process divided by the initial mass of the product. Both factors had two levels each: IMPD at 0.5 and 1.5 W/g and temperatures of 50 and 60°C. A central run for the study was conducted at 55°C and at 1 W/g. No pre-treatments were done to the cantaloupe slices in this study. For each run, about 100 g of freshly sliced cantaloupe pieces were prepared. The drying time of the product was the time required to reach final moisture content of 15% wet basis (wb). The data acquisition system was used to record and store process conditions measured by different sensors installed on the dryer. The mass of the samples, product and air temperatures, and microwave power were recorded at the intervals of 30 s. Data acquired was used for validation of models developed to forecast the moisture ratio.

4.2.4 Modelling of drying kinetics

4.2.4.1 Mathematical modelling

Predictive mathematical models found in the literature (Ertekin & Firat, 2017) were used to study the drying kinetics of cantaloupe slices in the microwave convective dryer (Table 4.1). The moisture ratio (MR) is defined as Equation (4.1):

$$MR = \frac{M_t - M_e}{M_o - M_e} \qquad 4.1$$

Where, M_t, M_e, and M_o are the moisture content at time t, initial moisture content and equilibrium moisture content, respectively. Since M_e was negligible in the case of drying in microwave cavity, the simplified equation 4.2 was used to calculate MR.

$$MR = \frac{M_t}{M_o} \quad 4.2$$

These models express the relationship between MR and the drying time. To fit the data to each model, Curve Expert Professional ver. 2.6.5 (Daniel G. Hyams, USA) was used for curve fitting.

Table 4.1 List of mathematical models tested in this study

Model Name	Model Equation	Reference
Lewis	$MR = exp(-kt)$	(Lewis, 1921)
Page	$MR = exp(-kt^n)$	(Agrawal & Singh, 1977)
Logarithmic	$MR = a\ exp(-kt^n)$	(Xanthopoulos et al., 2007)
Henderson and Pabis	$MR = a\ exp(-kt)$	(Hendreson & Pabis, 1961)
Wang and Singh	$MR = 1 + at + bt^2$	(Wang & Singh, 1978)
Two-term	$MR = a \exp(-k_o t) + b \exp(-k_1 t)$	(Henderson, 1974)
Two-term exponential	$MR = a \exp(-kt) + (1-a) \exp(-kat)$	(Sharaf-Eldeen et al., 1980)
Simplified Fick's differential equation	$MR = a \exp(-c(\frac{t}{L^2}))$	(Sacilik & Elicin, 2006)

4.3.4.2 ANN modelling

ANN model for estimating the MR was used to model the drying of cantaloupe in microwave-convective dryer. In this research, a previously trained Feed-forward model based on Adam optimization with 3 hidden layers and 64 neurons in each hidden layer was used. The network was trained using data acquired from Alcade-Garcia, F (2020).

The drying models and ANN were compared using the statistical parameters, coefficient of determination (R^2) and standard error of estimate (SEE) (equations4.3).

$$R^2 = \left(\frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}\right)^2 \quad 4.3$$

Where, x_i are the values of observed MR, $\bar{x}$ is mean of the values of the observed MR, y_i are the values of predicted MR and, $\bar{y}$ is the mean of the values of predicted MR.

$$SEE = \sqrt{\frac{1}{n-2}\left[\sum(y-\overline{y})^2 - \frac{[\sum(x-\bar{x})(y-\bar{y})]^2}{\sum(x-\bar{x})^2}\right]} \quad 4.4$$

Where, x and $\bar{x}$ are the observed value and mean of the observed values respectively and y and $\bar{y}$ are the predicted and mean of predicted values respectively, and n is the number of observations.

4.3.5 Quality Attributes

4.3.5.1 Total soluble solids

The total soluble contents were determined using a refractometer (Model r2 mini, Reichert, USA) for fresh samples of cantaloupe.

4.3.5.2 Colour analysis of dried cantaloupe

The colour of the dried product is an important property for estimating the efficacy of the drying. A Minolta chromameter (ChromaCR-300X, Japan) based on the CIE L*a*b* system was used. The measurements were displayed using 3 coordinates L*, a*, b*. The L* coordinate represents the lightness measured from 0 for white to 100 for black. The a* measures the greenness when negative and redness when positive and b* measures blueness when negative and yellowness when positive. Before taking the readings the chromameter was calibrated using a standardized white plate. The cantaloupe slices were then placed on the table and readings were taken by illuminating the meter perpendicularly. Five replicates were taken randomly after every drying run. The total colour change (ΔE), hue angle (H^o) and chroma (C) were represented using equations 4.5-4.7:

$$\Delta E = \sqrt{(L_o - L_*)^2 + (a_o - a_*)^2 + (b_o - b_*\,)^2} \qquad 4.5$$

$$C = \sqrt{(a_*)^2 + (b_*)^2} \qquad 4.6$$

$$H^o = \tan^{-1}\left(\frac{b_*}{a_*}\right) \qquad 4.7$$

Where, L_o, a_o and b_o are of fresh cantaloupe slices and L_*, a_* and b_* of dried cantaloupe.

4.3.5.3 Total phenolic content and antioxidant activity measurement

4.3.5.3.1 Methanol extraction

The methanol extraction was carried out according to the method described by (Palamanit et al., 2019). Two grams of dried samples were weighed, grinded and then diluted with 25 ml of 99% methanol v/v (Fisher Chemical, Trinidad) in a 50mL mixing tube. The mixture was then shaken at 175 rpm for 24 hours, while maintaining its temperature at 30℃. Afterwards, the mixtures were individually filtered through a No. 4 Whatman filter paper using vacuum filtration. The volume of the filtrate was adjusted to 25 ml with methanol and stored at 4℃ prior to analysis.

4.3.5.3.2 Total phenolic content

The total phenolic content (TPC) was measured using the Folin-Ciocaltaeau Assay (Wang et al., 2019). 500 µL of extract solution was mixed with 500 µL of 7.5% sodium carbonate solution and 1500 µL of deionized water. After that, 250 µL of Folin-Ciocalteau reagent was added and the mixture was incubated in the dark at room temperature for 30 minutes. The colour change was measured with a spectrophotometer (Ultrospec 2100pro, Amersham Biosciences, New Jersey, USA) at 765 nm. Gallic acid was used as a standard for preparing the calibration curve and TPC of cantaloupe extracts was expressed in microgram gallic acid equivalents (µg GAE/ g of dry matter). All samples were analyzed in triplicate.

4.2.5.3.3 Antioxidant activity

The antioxidant activity of dried cantaloupe was evaluated by DPPH radical-scavenging activity as reported by (Binsan et al., 2008) with slight modifications. l.5 mL of 0.15 mM DPPH (5.9 mg/100mL) prepared in 99% methanol was added to 1.5 mL of filtered extract. The reaction tubes were wrapped in aluminum foil and kept at room temperature in dark for 30 minutes. The absorbance was recorded at 517 nm using a spectrophotometer. The control was prepared in the same manner, except that methanol was used instead of the sample. The DPPH scavenging activity was determined against calibration curve for Trolox acid and expressed as µg TAE/ g of dry matter.

4.3 Results and Discussion

4.3.1 Drying analysis

The experimental process for the drying experiment is illustrated in Figures 4.1 and 4.2. The moisture content of the fresh samples was averaged at 88±0.9% (w.b.). Figure 4.3 represents the changes in moisture ratio of cantaloupe slices, for different drying conditions. Among the levels of temperatures and initial microwave power densities examined in this study, the drying time ranged between 153 to 207 minutes. The longest and shortest drying times were associated with air temperature of 50℃ for 0.5 W/g IMPD, and 60℃ for 1.5 W/g, respectively. It was observed that drying time reduced with increase in initial power density for the same air temperature. Such results were in accordance with the observations reported by Koné et al. (2013) for drying of tomatoes and by Ranjbaran and Zare (2012) for soybeans. For cantaloupe being dried at 50°C, the drying time was reduced by approximately 24% with an increased IMPD. However, samples dried at 60°C air reduced drying time by just 5% for higher power density.

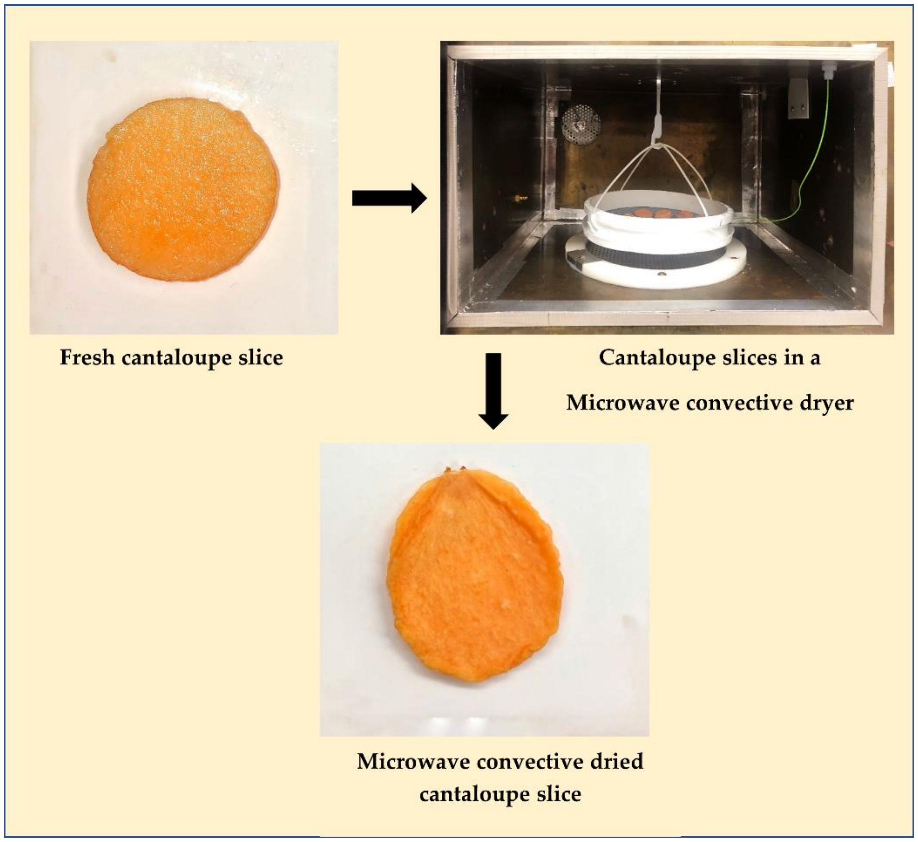
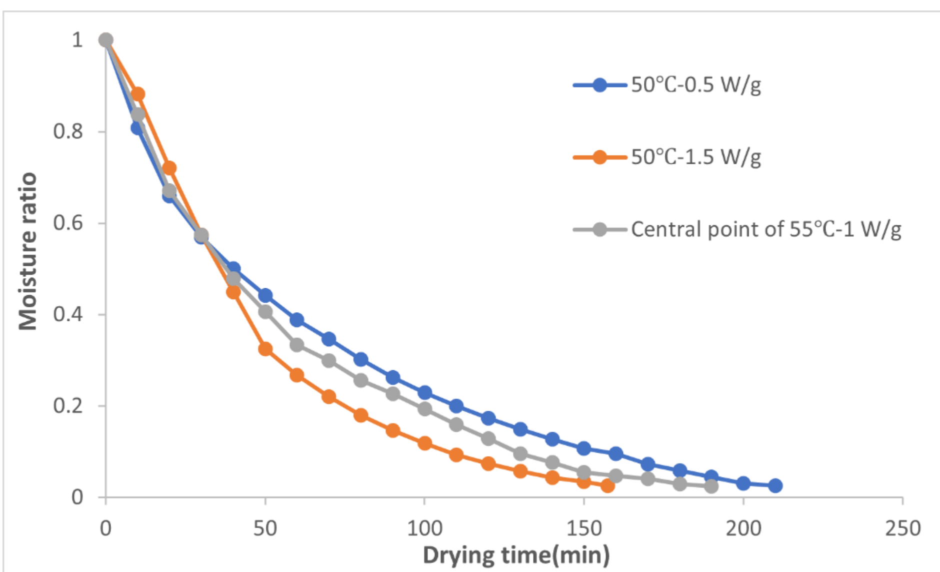
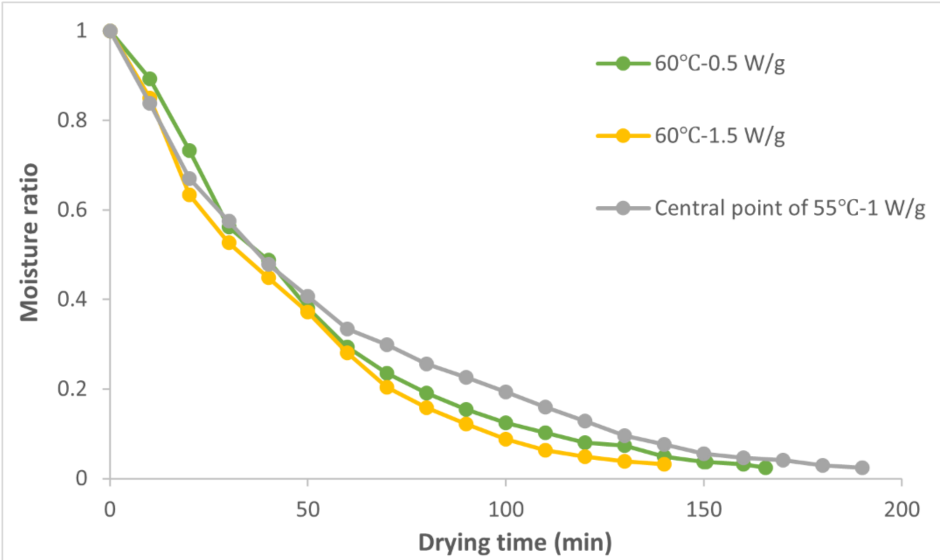


Figure 4.2 Process of drying of cantaloupe in a microwave convective dryer



(a)



(b)

Figure 4.3 Variation of moisture ratio against drying time for different IMPD at (a) 50℃ and (b) 60℃

A typical drying rate curve against moisture content dry basis for the experiment is illustrated in Figure 4.4. It is clear that of cantaloupe did not exhibit constant rate period of drying. However, two falling rate periods were vividly observed. Similar results were found in the literature for various biological products (Babu et al., 2018).

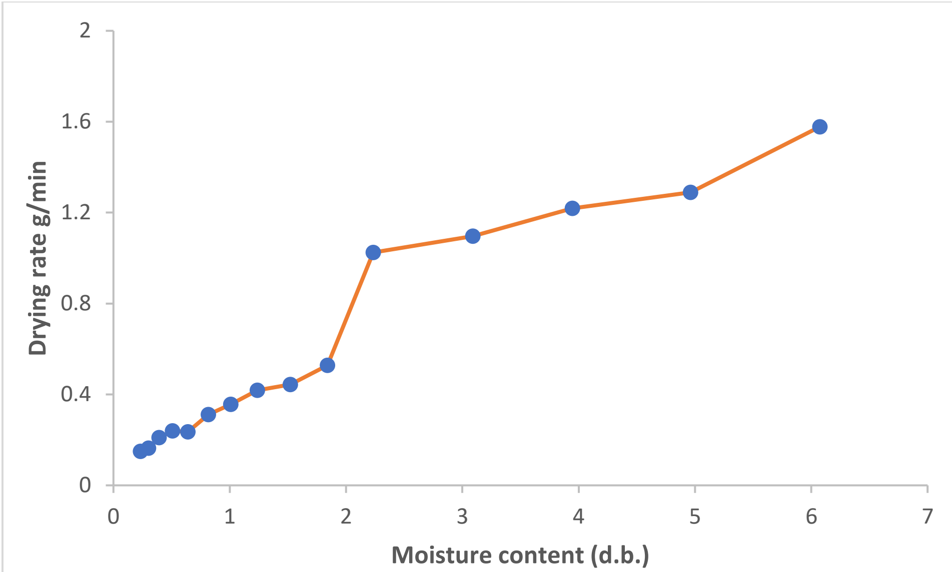


Figure 4.4 Sample drying rate curve for 0.5 IMPD at 50°C

4.3.2 Drying kinetics modelling

The moisture ratio of the drying experiment for cantaloupe was fitted to the mathematical models listed in Table 4.1 and a pre-trained ANN model. To evaluate the goodness of fit all the models were compared using R^2 and SE. The statistical regression results for all the different models, including the constants for mathematical results are given in Table 4.2.

Among all the mathematical models, it can be concluded that the two-term model gave the best simulation of the experimental data. The values of R^2 and SE for the two-term model ranged from 0.997 to 0.999, and 0.007 to 0.016, respectively. The aptness of the two-term model is further confirmed by the plot of experimental and predicted values of the study (Figure 4.5). From the insignificant values of regression coefficients for the Wang and Singh model it is apparent that it was the least performing model with R^2 values between 0.938 to 0.989.

The trained ANN model used for fitting the moisture ratio gave a decent prediction with the R^2 varying from 0.902 to 0.996. However, for all the temperature and power density levels examined, the mathematical models slightly outperformed the ANN model. Fig. 4.5 shows the comparison between predicted values from Two-term model, ANN model and experimental data for cantaloupe slices at the microwave-convective drying for the experimented temperature and IMPD levels. The results were in accordance with a study of drying of mango ginger in which semi-empirical models were found to give a superior prediction as compared to ANN (Krishna Murthy & Manohar, 2012). Another study was found of drying of watermelon rinds in which two-term model was the best fit semi-empirical model whose statistical parameters were comparable with the used ANN model (Fabani et al., 2021). Similarly, mathematical models predicted the drying process of timber better than the trained neural network (Ceylan, 2008).

Nonetheless, ANN modelling may be preferred to mathematical models due to their ability to generate a good estimate, simplicity, and low computational cost (Khan et al., 2020).

Table 4.2 Estimated values of statistical parameters for drying of cantaloupe in a microwave convective dryer for various conditions

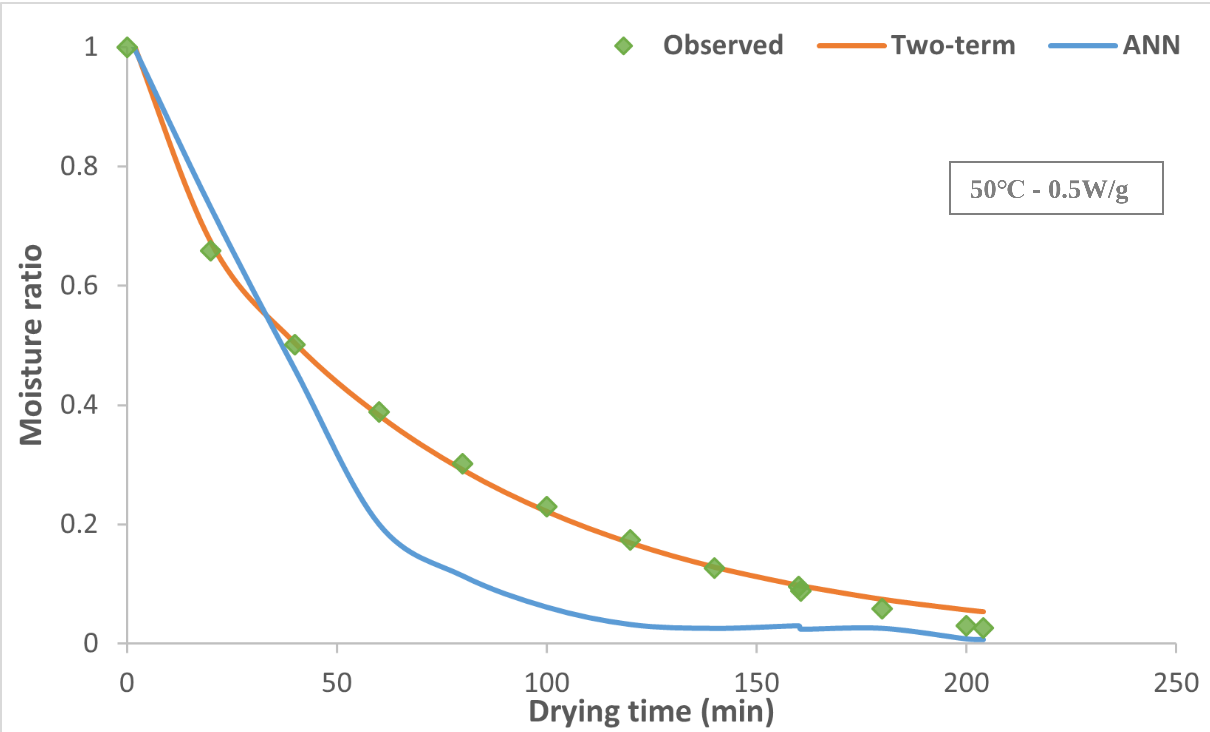
Temperature - 50°C Power density – 0.5 W/g																				
Statistics/ Constant values	**Models**																			
	Lewis	**Page**		**Logarithmic**			**Henderson & Pabis**		**Wang & Singh**		**Two-term**				**Two-term Exponential**		**Simplified Fick's equation**			**ANN**
	k	k	n	a	k	n	a	k	a	b	a	k_o	b	k_1	a	k	a	c	L	-
Constant	0.016	0.02	0.87	0.98	0.02	0.89	0.93	0.01	-0.01	3.5E-5	0.87	0.01	0.16	0.13	0.13	0.11	0.93	2.9E+03	443	-
R^2	0.987	0.995		0.995			0.993		0.938		**0.998**				0.997		0.994			0.939
SEE	0.027	0.016		0.015			0.019		0.059		**0.011**				0.012		0.018			0.080

Temperature - 50°C Power density – 1.5 W/g																				
Statistics/ Constant values	**Models**																			
	Lewis	**Page**		**Logarithmic**			**Henderson & Pabis**		**Wang & Singh**		**Two-term**				**Two-term Exponential**		**Simplified Fick's equation**			**ANN**
	k	k	n	a	k	n	a	k	a	b	a	k_o	b	k_1	a	k	a	c	L	-
Constant	0.023	0.01	1.15	1.05	0.02	1.08	1.08	0.02	-0.01	6.1E-5	-0.15	0.21	1.14	0.02	1.08	691	1.08	691	175	-
R^2	0.989	0.995		0.997			0.996		0.986		**0.999**				0.996		0.996			0.996
SEE	0.028	0.017		0.013			0.016		0.033		**0.010**				0.018		0.016			0.020

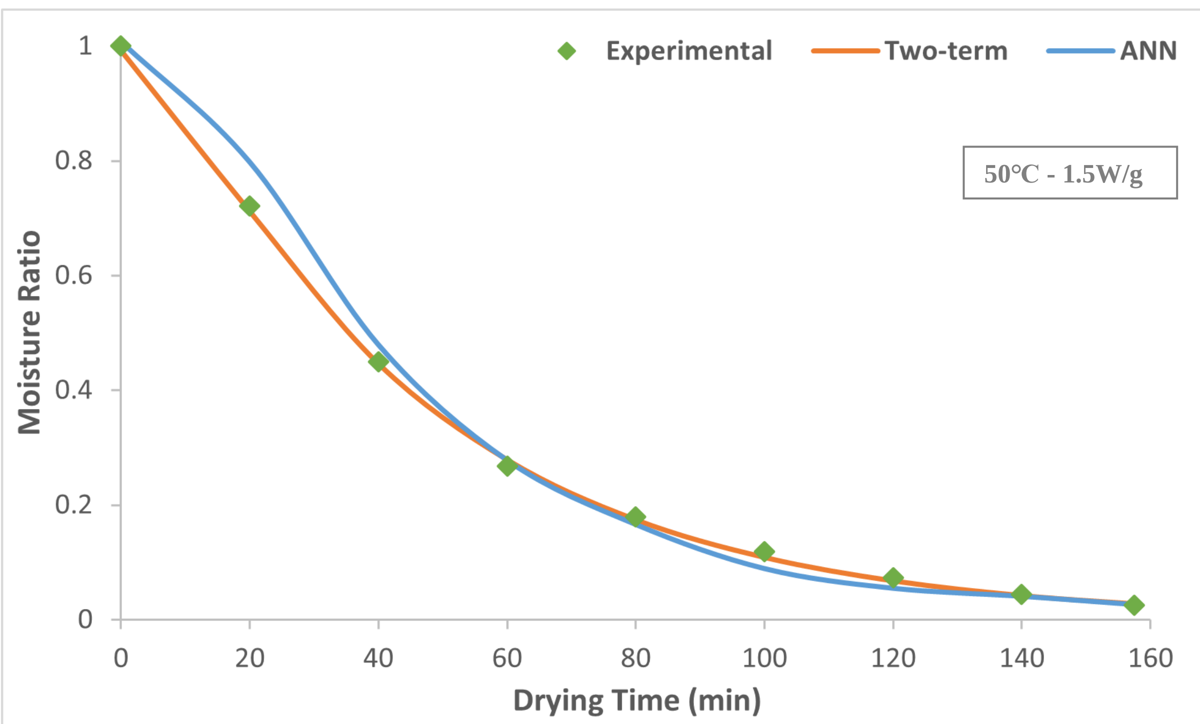
Temperature - 55°C Power density – 1.0 W/g																				
Statistics/ Constant values	**Models**																			
	Lewis	**Page**		**Logarithmic**			**Henderson & Pabis**		**Wang & Singh**		**Two-term**				**Two-term Exponential**		**Simplified Fick's equation**			**ANN**
	k	k	n	a	k	n	a	k	a	b	a	k_o	b	k_1	a	k	a	c	L	-
Constant	0.0170	0.02	0.97	1.01	0.02	0.95	0.93	0.017	-0.01	4.26E-5	0.09	0.10	0.94	001	0.007	2.49	0.99	3720	460	**-**
R^2	0.995	0.996		0.996			0.995		0.965		**0.997**				0.996		0.996			0.9025
SEE	0.016	0.015		0.015			0.016		0.048		**0.014**				0.016		0.016			0.086

Temperature - 60°C Power density – 0.5 W/g																				
Statistics/ Constant values	**Models**																			
	Lewis	**Page**		**Logarithmic**			**Henderson & Pabis**		**Wang & Singh**		**Two-term**				**Two-term Exponential**		**Simplified Fick's equation**			**ANN**
	k	k	n	a	k	n	a	k	a	b	a	k_o	b	k_1	a	k	a	c	L	-
Constant	0.02	0.01	1.16	1.03	0.01	1.11	1.08	0.02	-0.02	5.3E-5	1.15	0.02	-0.15	0.15	0.0004	42	1.08	0.01	0.74	**-**
R^2	0.990	0.997		0.998			0.996		0.989		**0.999**				0.990		0.997			0.985
SEE	0.027	0.011		0.009			0.014		0.028		**0.007**				0.028		0.014			0.050

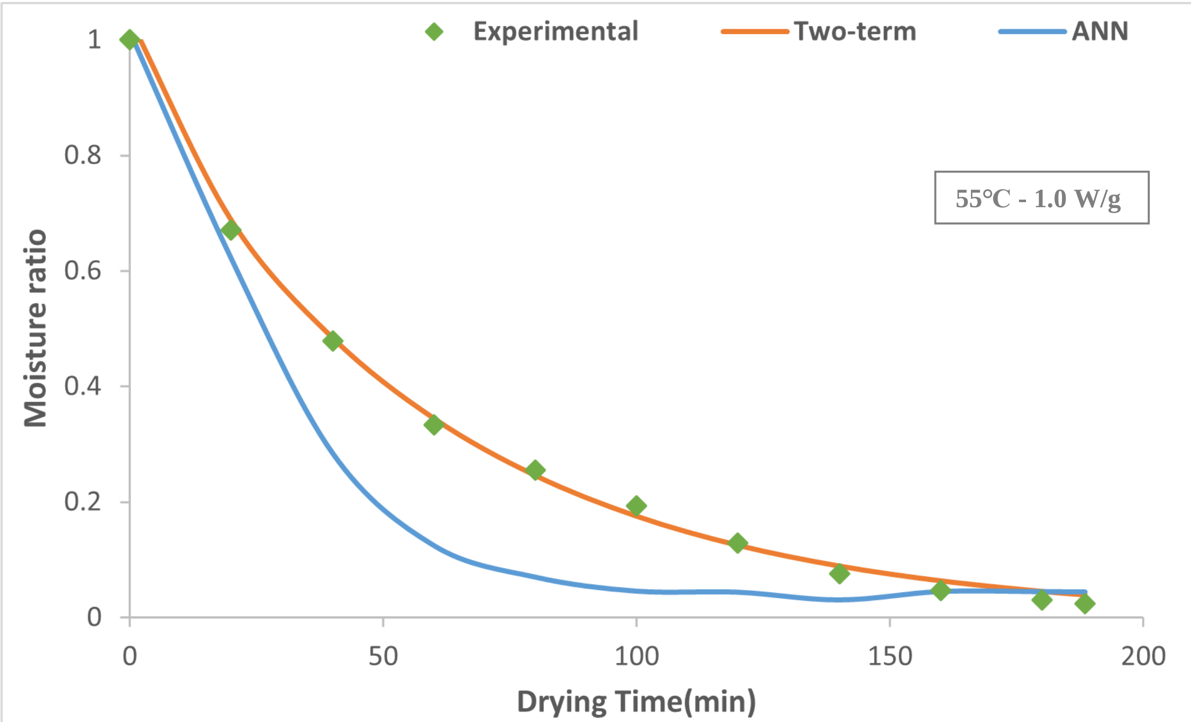
Temperature - 60°C Power density – 1.5 W/g																				
Statistics/ Constant values	**Models**																			
	Lewis	**Page**		**Logarithmic**			**Henderson & Pabis**		**Wang & Singh**		**Two-term**				**Two-term Exponential**		**Simplified Fick's equation**			**ANN**
	k	k	n	a	k	n	a	k	a	b	a	k_o	b	k_1	a	k	a	c	L	-
Constant	0.01	0.01	1.11	1.01	0.01	1.08	1.05	0.02	-0.01	6.5E-5	11	0.03	-10	0.03	0.0006	34.1	1.05	109.9	68.9	**-**
R^2	0.992	0.996		0.996			0.975		0.987		**0.998**				0.996		0.995			0.993
SEE	0.024	0.017		0.017			0.019		0.030		**0.016**				0.023		0.018			0.023


Observed
Two-term
ANN
50°C - 0.5W/g
Moisture ratio
Drying time (min)
1
0.8
0.6
0.4
0.2
0
0
50
100
150
200
250

(a)

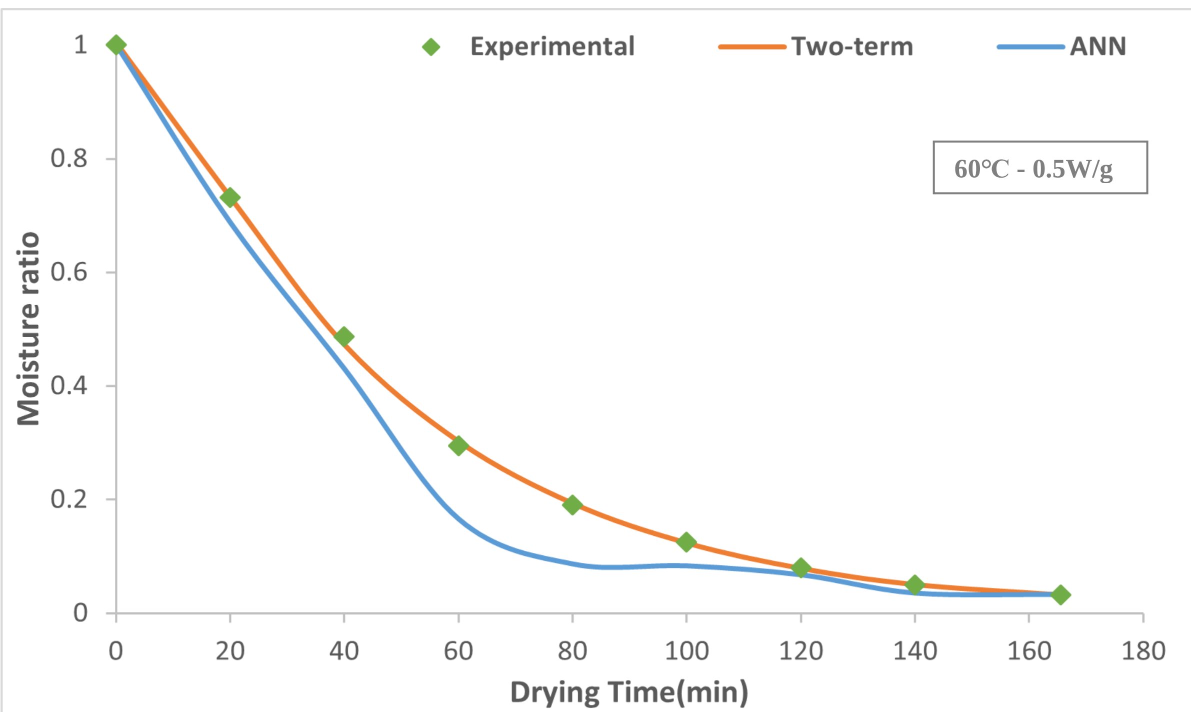

Experimental
Two-term
ANN
50°C - 1.5W/g
Moisture Ratio
Drying Time (min)
1
0.8
0.6
0.4
0.2
0
0
20
40
60
80
100
120
140
160

(b)



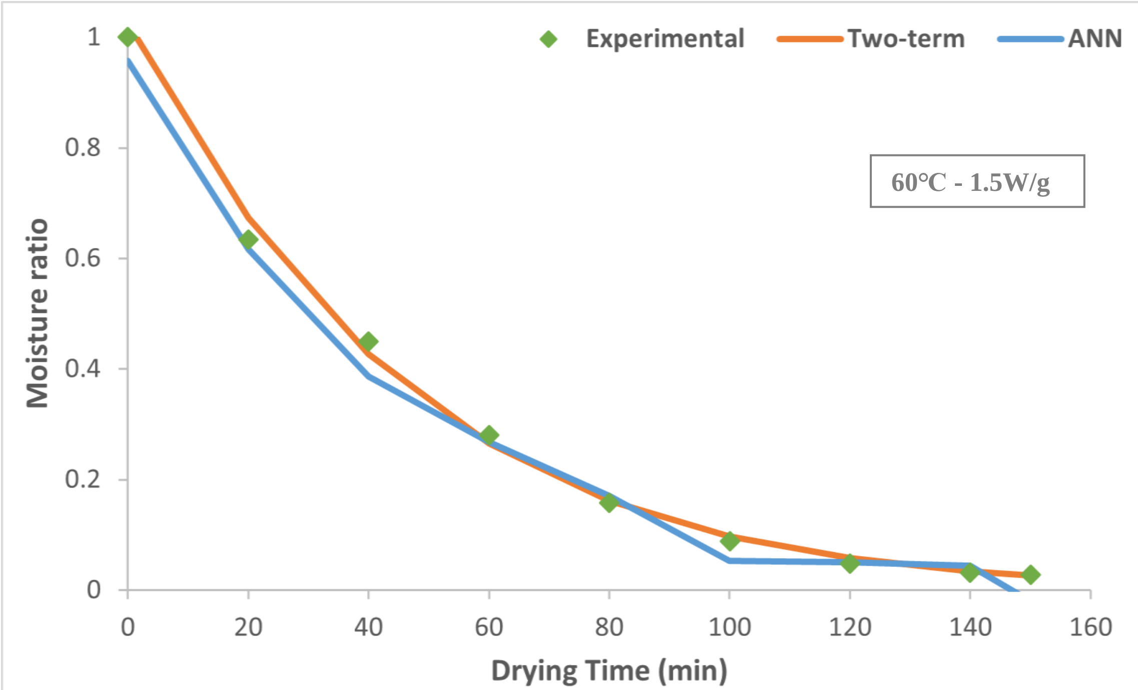
Experimental
Two-term
ANN
55°C - 1.0 W/g
Moisture ratio
1
0.8
0.6
0.4
0.2
0
0
50
100
150
200
Drying Time(min)

(c)



Experimental
Two-term
ANN
60°C - 0.5W/g
Moisture ratio
1
0.8
0.6
0.4
0.2
0
0
20
40
60
80
100
120
140
160
180
Drying Time(min)

(d)



(e)

Figure 4.5 The best mathematical model and ANN model fitting to the drying curve of cantaloupe slices dried at various levels of temperatures and IMPD

4.3.3 Quality Attributes

4.3.3.1 Total soluble solids

The total soluble content measured by a refractometer ranged between 12 to 15°Brix

4.3.3.2 Colour measurement

The change in colour parameters, L*, a*, and b*, of cantaloupe for different initial power densities and temperature levels was measured during the microwave-convective drying process. All the parameters were seen to increase after drying indicating increase in darkness, yellowness, and intensification of redness of the sample. The total change in colour, hue and chroma of the dried product are presented in Table 4.3. The change in colour was lowest for 50°C with 0.5 IMPD and highest for 60°C with 1.5 IMPD. The same was true for Hue and Chroma.

Table 4.3 Colour values of dried cantaloupe slices in microwave convective dryer

IMPD (W/g)	Temperature (°C)	ΔE	H°	C
0.5	50	15.22	1.23	52.96
1.5	50	15.67	1.25	51.38
1	55	19.23	1.26	57.36
0.5	60	15.76	1.24	54.07
1.5	60	19.63	1.24	56.78

4.3.3.2 Total phenolic content

A calibration curve (Figure 4.6) was used to express the TPC of extract in µg GAE/ g of dry matter. The values of TPC obtained are presented in Figure 4.7. It was observed that the TPC showed a notable increase after the drying process, especially at high IMPD. This might be due to disintegration of the cellular matrix during the drying process which releases the bound phytochemicals. Similar values were reported by Phisut et al. (2013) for osmotically dehydrated cantaloupe slices. However, Alcade-Garcia,F (2020) stated values of TPC which were in the range of 100-400. The values were comparatively lower than what was reported in the present study.

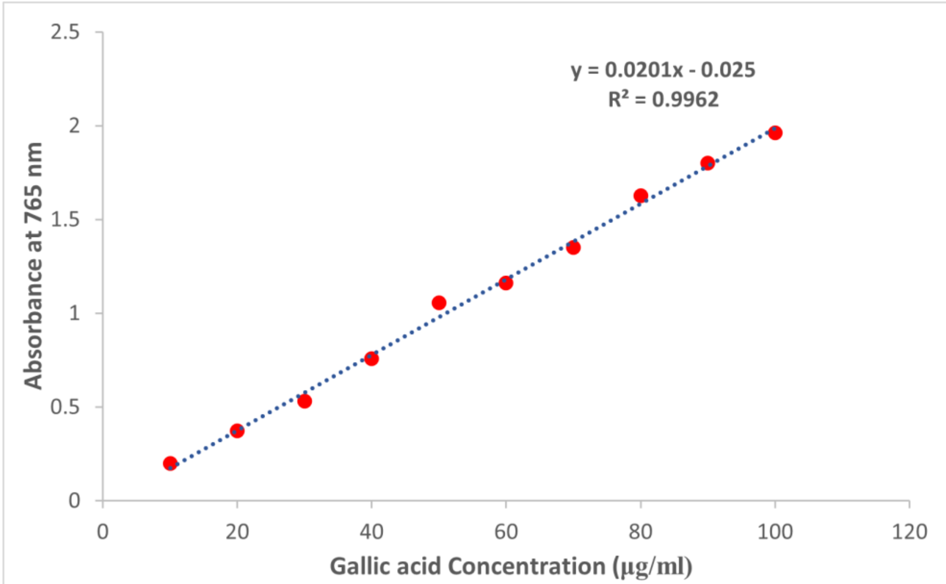


Fig 4.6 Calibration curve of Gallic acid

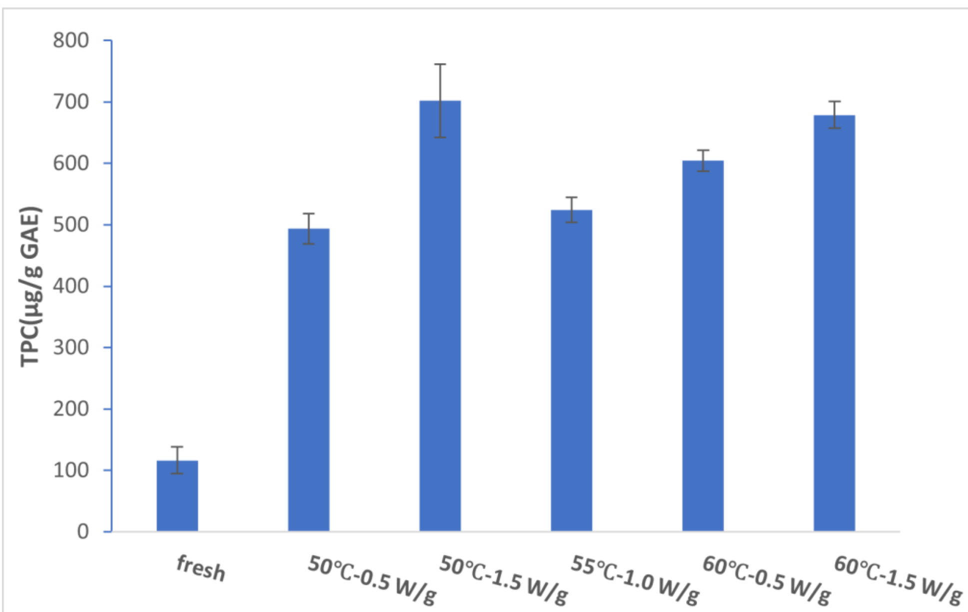


Fig 4.7 Total phenolic content values for different drying conditions

4.3.3.3 DPPH scavenging activity

The DPPH scavenging activity was measured against the calibration curve of Trolox acid (Figure 4.8) and was expressed as µg of TAE / g d.b. The calculated DPPH is reported in Figure 4.9. The

DPPH increased for all drying trials as compared to fresh samples. However, the increase was not very notable and ranged from 1%-6%.

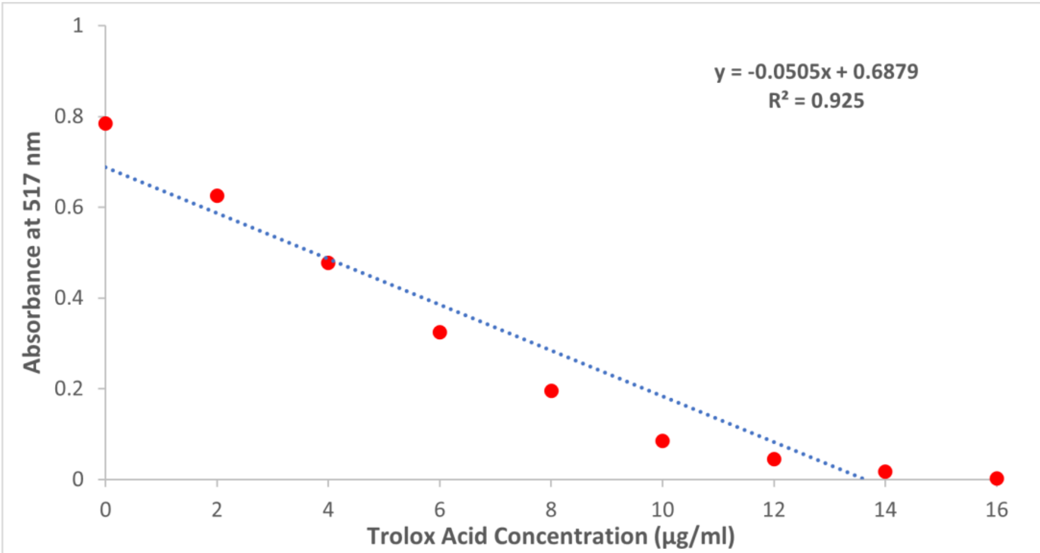


Fig 4.8 Calibration curve of Trolox acid

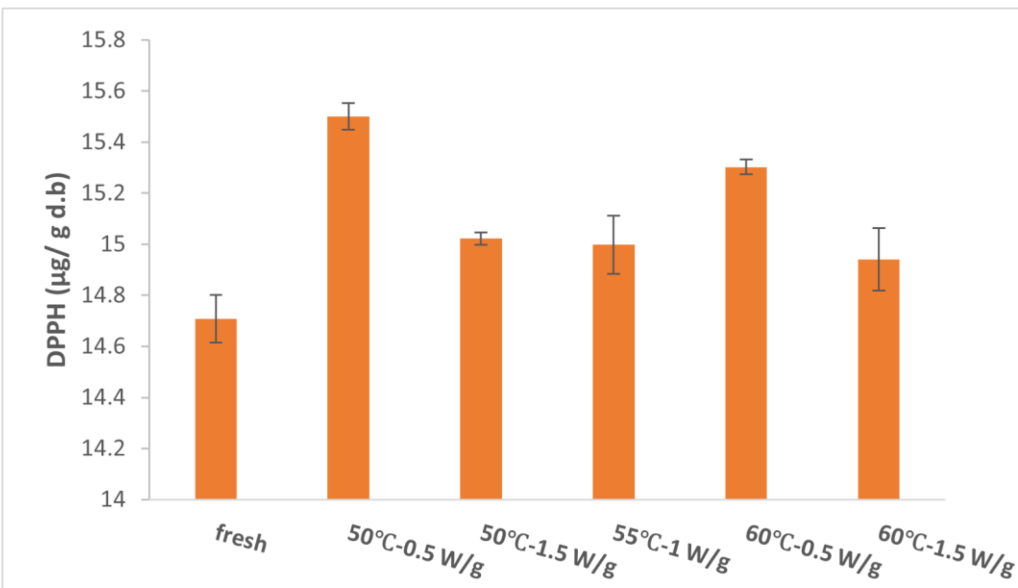


Fig 4.9 DPPH values for different drying conditions

4.4 Conclusion

The drying behaviour of cantaloupe in a microwave convective dryer was investigated by varying the air temperature and initial microwave power density. It was found that with increase in the temperature and initial power density the drying time decreased. The drying rate exhibited a falling rate period while the constant rate period was absent. To model the drying kinetics of cantaloupe eight mathematical models from the literature along with a pre trained Artificial Neural Network were investigated. The two-term model gave the most accurate estimate with R^2 from 0.997 to 0.999 whereas the ANN gave an R^2 between 0.902 to 0.996. The L^*, a^* and b^* parameters increased with drying. The colour change was lowest for drying trial with a low level of temperature and IMPD, and as such, it was the closest to the fresh fruit colour. The phenol content and antioxidant activity were calculated and were seen to rise notably after drying.

CHAPTER V

SUMMARY AND CONCLUSION

5.1 Summary

Considering the current surge in the use of artificial neural networks to model nonlinear processes, the current study examined the application of ANN to the drying process. Despite the fact that machine learning has been around for a long time, contemporary hardware advancements have made the training of ANNs less time consuming. A decision maker who wants to know how uncertain a particular model is might benefit from being able to sample several alternative initializations to see how much variation there is in the model's output.

The first objective in this study was to examine the pertinence of use of neural networks to model the moisture ratio and product temperature of cantaloupe in a microwave convective dryer. Many different architectures were sampled for recurrent and feed forward networks. The data from 13 drying trials was used to train and assess the trained network. The FNN was trained using a backpropagation algorithm while the recurrent network had a feed back loop to use the predicted output as one of the inputs. Among all the architectures tested an FNN with 3 hidden layers and 64 neurons each and batch size of 32 gave the best performance. Overall, FNNs performed better than LSTMs. Both types of networks showed the capability to give a superior prediction of the moisture ratio as compared to the product temperature. Also, the minimum data size required for training of the networks was calculated and it was found that LSTM needed more data points to perform satisfactorily.

The second objective in this study was to investigate the drying kinetics of cantaloupe in a microwave convective dryer for different combinations of inlet air temperatures (50℃ and 60℃)

and initial microwave power densities. A central point with inlet temperature of 55℃ and initial microwave power density of 1W/g was also recorded. 8 mathematical models and a trained ANN model was used to demonstrate the changes in moisture ratio during the drying process. It was found the two-term model best described the drying behaviour of cantaloupe. The changes in colour, hue angle and chroma of the dried product was also reported. The total phenolic content and antioxidant activity values increased in the dried samples. However, the increase was more notable for the phenolic content as compared to the antioxidant values.

5.2 Future Recommendations

1) Additional network topologies and optimization algorithms can be evaluated in order to improve accuracy even further.
2) An attempt to model the colour, specific energy consumption of the drying process using ANN can be conducted.
3) Further, integrating different machine learning techniques and application of computer expert systems such as fuzzy logic can be done to compare with the classical modelling approach.
4) Moreover, the effect of various pre-treatments on the quality of dried cantaloupe in a microwave convective dryer can be studied.

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