Chapter 2

2. Review of Literature

This chapter consists of references of the work that has helped in better understanding of the concept of processing rice, ageing of rice, application of NIRS for quality assessment, NIR-based process analysis, ML techniques for predictive modeling, low-cost portable sensors, and other similar topics.

2.1 Parboiling of rice

Production of high-quality safe food is a concern for the food industries. Likewise, rice industries have a huge demand to meet the consumption of people. Rice goes through a process of direct milling of paddy after drying to a moisture level for safe storage, or else parboiling. Parboiling involves soaking, steaming, and drying. Each step of this process is crucial in manufacturing good quality rice [1].

The basic process of parboiling has remained the same throughout the years. Soaking is done for the diffusion of water along with nutrients into the endosperm, steaming for gelatinization of the starch, and lastly drying to a storable moisture content [2]. However, the variation in conditions differs in accordance with the requirement of the final product [3]. It is cooked or processed in different ways, and every task and all parameters have a major impact on its eating quality. In addition, geographical location has impacts on rice characteristics [4]. For example, East Asian countries mostly prefer short sticky rice, whereas South Asians prefer parboiled sticky rice [5]. Rice grown in the state of Assam or northeastern states are mostly of medium size and bold or slender in shape distinguishing themselves from the rice preferred and grown in other parts of the country, which are mostly long in size and slender in shape.

Parboiling of rice has been found to increase the cooking time. The reason for this is due to the structural changes during parboiling i.e., the internal fissures and cracks in endosperms are filled making the structure more compact [6]. Treatment like instant controlled pressure drop has a very high impact on the quality attributes like less breakage during milling and higher water diffusion in soaking which is very desirable in terms of cooking quality [7]. The pressure-parboiling process reduces the processing time further.

Paddy is usually soaked at room temperature for roughly 72 hours during a single boiling process. Paddy that has been soaked, was dried by steaming after the soak water has been drained. Although this method is inexpensive and simple to use, there is no safeguard against microbial fermentation, which could give the product an unsavory flavor. The double boiling procedure includes a step of steaming before placing the paddy in the soak water, which heats the water. The soaking process is then repeated at ambient temperature, but for a shorter period, around 36 hours. The unsoaked water is drained, then steamed and dried. While the shortened soaking time and the ability to achieve an aged texture are advantages over a single steaming operation, the possibility of fermentation leading to off-flavor development remains as well as the chance of grain bursting [8]. The CFTRI procedure, which is a faster process with only about 3 hours of soaking, is performed at a soak water temperature of about 70°C, a temperature close to the gelatinization temperature. After soaking, the normal process of draining the soaking water, steaming, and drying follows. While this process offers benefits such as reduced soaking time and elimination of potential off-odor development, the process is expensive and operates only in batch mode [9].

In Africa and South Asia, for example, fuelwood and direct rice husk combustion have been the main sources of energy for parboiling and steaming. Many local parboilers rely primarily on solar energy to dry their paddy. However, medium-scale parboiling has also been done in parts of Asia using a combination of sun and mechanical drying approaches [10]. Kwofie et al. [10] reviewed the concept, systems, energy supply, energy consumption, and effects of the use of energy on the quality of the product of the parboiling process. As per the study, the wide variation between theoretical parboiling energy demand and therefore the laboratory and field measuring were considered a sign of inefficient systems. Parboiling of de-husked rice or brown rice reduced energy consumption to 40%, thus saving the tough drudgery and resources of small manufacturers, making it a more economical process, and moreover enhancing the organoleptic properties [11]. An investigation based on the utilization of superheated steam-fluidized bed drying to generate fully parboiled glutinous rice in just one method as opposed to two conventional methods (steaming and drying at the same time) gave a better head rice yield, lighter color, and softer texture [12].

Soaking is an important and foremost step in parboiling. Rice starches under normal conditions have a moisture content of about 12-14% (wb). During soaking, cold water can enter the amorphous starch region without disturbing the micelle, and a maximum water content of 30%

(wb) is reached. On allowing the rice mixture to be heated, the intermolecular hydrogen bonds are broken, and the granules absorb more water and swell. This causes the loss of birefringence. This leads to the leaching of amylose and the formation of gel while steaming rice [13]. Isothermal soaking experiments were carried out at different temperatures in different studies. The soaking temperature on rough rice was checked at 65, 70, and 75 °C for 3 h, where the higher temperature sample had more influence on the pasting temperature [14]. Water uptake was also studied for brown rice within the soaking temperatures of 25, 35, 45, 55, and 65 °C, which gave a clear idea that diffusion coefficients were a strongly increasing function of moisture content [15]. However, it was suggested that soaking above the temperature of 60 °C facilitates gelatinization over hydration [16]. Cheevitsopon and Noomhorm [17] performed diffusion kinetics of water at soaking temperatures ranging from 30 to 60 °C and found the diffusion coefficient to be ranging from 5.30 x 10^{-11} to 1.56 x 10^{-10} m^2/s.

Soaking lets hydration of the kernels fill the fissures inside the kernels, steaming involves heat treatment that causes starch gelatinization. Dietary starches are a mixture of two structurally distinct components: amylose and amylopectin. Amylose and amylopectin are arranged radially inside the starch granules, containing both non-crystalline and crystalline structures in alternate layers. In the case of undamaged starch grains, insolubility is high in cold water but can absorb water reversibly if the temperature is increased and starts leaching out in water. As a result, when heated with water, starch granules undergo leaching and start forming gel and this process is called gelatinization. Therefore, gelatinization can be defined as a method in which starch particles are heated in water until they break, collapse, and produce a paste or gel. In alternative words, gelatinization is the breaking of the molecular order among the molecules. The kernels start to swell speedily and lose birefringence at a particular temperature which is known as gelatinization temperature. The gelatinization temperature of rice is generally around 65-73 °C [18]. A study comparing both the gelatinization temperatures and endothermic energy of brown, and rice-milled flours with high, moderate, and low amylose contents revealed that brown rice flour generally had higher gelatinization temperatures than milled rice flour. The same investigation also stated that mean endothermic energy is more with a decrease in amylose content [19].

Drying is the last step and most crucial step for proper storage. Drying is one of the oldest phenomena for food preservation that involves both heat and mass transfer simultaneously [20]. The primary steps of parboiling, which involves soaking and steaming, can be categorized as moisture absorption processes. The purpose of drying is to remove the moisture from the brown rice for further storage without any spoilage. The desirable moisture content is 12-13% (wb) [20]. The color of cooked rice was affected by drying temperature, but it insignificantly affected shrinkage and the rehydration capability of dried cooked rice.

Dutta and Mahanta (2014) reviewed the traditional status of the rice varieties in Assam. As reported, the Indian state of Assam produces a vast range of rice types, some of which are conventionally processed into exotic parboiled low-amylose rice products such as *Hurum*, *Komal Chaul*, *Bhoja chaul*, and *Sandahguri*, which have both ethnic and commercial significance [21]. They had optimized a laboratory scale method for developing ready-to-eat *Komal Chaul*-based products that involved initial hot soaking of paddy for 1 and 3 min and tempering by allowing it to cool temperature for 18 h, pressure steaming for 20 min, followed by drying at room temperature for 48 h and finally milling [22]. Wahengbam and Hazarika (2018) suggested a brown parboiling method for the production of *Komal Chaul*; this method implied soaking of dehusked *Chokuwa* at 60 °C for 90 min, open steaming of 20 min or pressure steaming, followed by drying to a moisture content of 12% (wb) [23].

Mohapatra and Rao, (2005) reported the influence of cooking qualities on the degree of milling like with a 3.3% increase in the degree of milling optimum cooking time decreased by 4 min. The degree of milling showed an increased effect on the physical properties of rice which is due to the removal of the bran layer. Grain thickness correlated in a decreasing manner with optimum cooking time, and cohesiveness and positively with water uptake ratio, volume expansion ratio, length expansion ratio, hardness, and adhesiveness, however, amylose content has a negative impact on optimum cooking time, hardness adhesiveness, and positive impact on water uptake ratio, volume expansion ratio, length expansion ratio, cohesiveness, and adhesiveness [24].

So, therefore an easy-to-handle and reliable technology for monitoring the stages of parboiling is required for quality products. Earlier, mathematical models were used to estimate overall processing conditions for the desired palatability of rice. Models are required to optimize the cooking time and water concentration for the best cooking. Earlier works give us ideas about how kinetic models like shrinking core models, diffusion equations, and empirical models mapped to image data provide us an insight into the intrinsic reactions while cooking, thus making us understand cooking fundamentally [25]. ML techniques like Principal Component Analysis (PCA) ensembled with polytomous logistic regression can help us predict the sensorial stickiness of rice in terms of textural attributes which were mapped with apparent amylose content, gelatinization temperature, and rapid visco analysis (RVA) parameters [26]. Reports have been found that use artificial intelligence-based systems for the development of prediction of soaking characteristics. It helps us to characterize and improve the soaking process, build grain processing machinery, and forecast water absorption as a function of temperature and time. The models that perform very well for estimating hydration behavior are Adaptive Neuro Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and Variable diffusivity approach. ANFIS is the amalgamation of neural network and fuzzy logic where it incorporates learning abilities from neural networks and inference capabilities like modifying the membership function for desirability. The hydration behavior of wheat can be modeled by an Adaptive neuro-fuzzy inference system (ANFIS), one of the most widely used artificial intelligence simulation frameworks [27]. Recently, it was found that ANN outperformed other predictive models for determining the hydration rate [28]. Also, the diffusivity approach is studied for better fundamental understanding [29].

2.2 Ageing of rice

Aged rice is preferable due to its low glycemic index (GI) rice. Low GI type of food is usually related to a lower postprandial response of glucose and insulin. Reports suggest that consuming aged rice would have a lower risk of diabetes mellitus [30]. Although rice ageing is not fully understood, the noticeable factors need to be studied with the eating and cooking quality.

Rice is generally devoured as cooked rice, there's a prerequisite for the capacity of rice. As a result, rice gets matured which leads to physicochemical changes. To be exact, rice maturing begins sometimes near harvesting [31]. Prior reports had affirmed rice composition, pasting properties, thermal properties, and texture are influenced by aging [32, 33, 34]. Lipids, protein, and starch changes moreover take place but at a negligible rate as portrayed by Chrastil and Zarin, (1992) [35]. The normal atomic weight of peptide subunits of oryzenin increments amid capacity, the rate of higher atomic weight increments whereas the rate of lower atomic weight diminishes.

Ageing leads to changes in textural properties. As reported by Zhou et al. [36] amylograph peak viscosity was found to be higher in new rice, whereas in other cases it was totally diverse. After an initial increase at the primary six months, the setback viscosity started to diminish over the three-year period of study. Pasting properties, color, flavor, and composition change while ageing, but there were no significant changes found in the textural and viscometrical parameters at different packaging conditions.

Changes during ageing were studied at 4 °C and 37 °C by Zhou et al. [34]. At 37 °C, the RVA peak was quite high, suggesting a quick ageing process. Coarser morphology for SEM at 4°C compared to 37 °C. Consequently, the ageing process decreased the gruel solid mass into the residual cooking water, further confirming that the starch grains in the aged rice grains caused less leaching of amylose and moreover less hydration and swelling. Cell wall residue analysis indicated that rice stored at higher temperatures caused a significant increase in the amount of cell wall residue throughout storage, which might be due to the cell wall structure of rice grains ageing and becoming more lignified. Thus, it is assumed that the ageing method ends up in the cell walls turning more strengthened and lignified, which makes the rice grain more organized in its structure and later reduces starch granules' disruption and molecules' natural process throughout the cooking.

Parboiling seldom changes the order of the helical structure, side chain distribution, or the double helix structure, however, crystallinity is affected by parboiling. A study on the multi-scale structural changes and in vivo digestibility of parboiled rice reported that the crystallinity changed from A to A+V or B+V relative crystallinity decreased by 24% approximately. The in vivo study also indicated that parboiling significantly reduced the glycemic index of rice to a medium level [38]. Furthermore, in the process of ageing, the rice structure gets progressively organized and reinforced. According to previous work [39], the RVA and Differential Scanning Calorimetry (DSC) data indicated that rice aged faster at higher temperature storage. This was due to the reason that in aged rice the starch granules were less likely hydrated and swollen. Some reports cite the acceleration of ageing in rice is due to the presence of endogenous amylase enzymes. Studies also suggested that the presence of oryzenin enhanced ageing giving more rigidity to the starch structure. Interactions between starch granules and protein molecules give the granule stiffness or strength in aged rice samples because of increased protein disulfide bridges and inter/intra protein molecule cross-linking. Prolamins and glutelin rice storage proteins were reported to decrease during ageing [40].

The starch content of rice is generally considered an intrinsic component; therefore, the change in starch content over time during rice aging is of little significance. According to Dhaliwal [41] and Cao et al. [42] enzymatic degradation of starch might occur during storage of aged rice. It was observed that aged rice had a slight increase in reducing sugar content, indicating the possibility of enzymatic degradation of starch during storage.

In rice, the changes in its pasting properties, as measured with a thermo-viscometer and particularly by amylography, are one of the most sensitive indices of the ageing process. Changes in rice paste and thermal properties after storage have been extensively studied and the results imply that changes in rice paste, and thermal properties are strongly dependent on storage temperature and storage time. In rapid visco analysis, breakdown viscosity, and peak viscosity are the maximum sensitive indices for comparing the rice ageing process [43, 32]. Reduced breakdown and gradual disappearance of a well-defined peak in aged samples were the most notable effects of ageing. The gelatinization kinetics study confirmed that better temperature storage resulted in a surge within the breaking factor temperature for the aged rice when compared to its clean rice. The breakdown point divides the gelatinization technique into regions: disruption of the amorphous vicinity and crystalline vicinity [36, 44].

Environmental factors like temperature and moisture are dominant factors of rice yellowing. Yellowness indicates primary and secondary metabolism. The upregulation of flavonoids is the direct cause of rice yellowing. Aeration and cooling can prevent rice from yellowing during storage [45]. Airtight storage of rice appears to be a more practical and beneficial way to maintain rice quality and control insect mortality during storage. The use of hermetic storage has been proposed to lead to a safe, pesticide-free, and sustainable storage method suitable for rice seeds. Comparing the storage of rice in IRRI airtight bags or ordinary woven polyethylene bags at room temperature for 9 months and found that dry rice airtight storage could greatly improve the overall quality of rice, including insect mortality, gas content, moisture content and mass of thousands of grains, porosity, hardness, whiteness, total milled rice yield, brown rice yield, gelatinization temperature, amylose, crude protein, crude fat, free fatty acids and sensory characteristics [46].

2.3 NIRS and its application

NIR spectra are electromagnetic frequencies in the range of 780-2500 nm. NIRS is usually preferred over conventional chemical analysis for its non-destructive nature and can easily generate spectrum from solid samples (both solid and liquid) without any initial treatment. The rapidness of this method has made speedy characterization possible without any use of chemical, thus making it a reagent-free methodology when calibrated against the primary reference method [47].

The principle behind molecular spectroscopy is the fundamental vibration of molecules due to combination and overtone bonds, resulting in absorption or reflectance of light. The bonds that are recognized in the infrared region are OH, CH, CO, NH, and other covalent bonds. NIR absorption bands are also very wide and highly overlapped because they are the overtones and also orders of magnitude weaker than the fundamental bands [48].

NIRS is usually preferred for its non-destructive nature and can easily record spectra from solid and liquid samples without any pre-treatment [49]. Wider findings on proof of concept at the research level are more limited to research fields but NIR application has expanded to the food industry though very limited [50]. Unlike other non-destructive techniques, NIR is preferred for its cost-effectiveness. Its instrumentation involves simple mechanics and robust sensors making it suitable for online process analysis [51].

In fact, NIR is not a novel technique. It was first used in 1950 but was popularized by Karl Norris at the USDA in the 1970s. It was reported that in 1974 Canadian Grain Commission used the NIRS technique for protein estimation as an alternative to the Kjeldahl method. They saved a million dollars thus proving it to be a cost-effective method [47]. Back in 1995, Principal Component Regression was used to calibrate NIR spectra of salmon filets for estimation of moisture, protein, and fat [52], thus showing that multivariate analysis was used long back for calibrating spectral data.

At present times, there are advancements in the technologies for instrumentation and it has resulted in the manufacturing of portable spectrophotometers that are able to give spectral data without much initial processing, making it better for rapid analysis [53]. It uses ML as a calibration tool to map a link of NIRS-based measurements into desirable extrinsic measures of food quality that use our smartphone as a visualizing medium for output. In this study, we plan to briefly discuss the applications of ML as an enabler for calibration and validation tools of NIR spectroscopy. This will surely give us insight into how we can apply ML techniques combined with NIR to provide better solutions to the food industry in quality analysis and process monitoring.

NIR spectroscopy has been used for food analysis for several reasons like a non-destructive, rapid response, cost-effective, and environmentally friendly. Here in this section, the recent application of ML techniques and their feasibility in food quality is discussed.

NIRS in combination with the multivariate technique is a better alternative to laborious chemical analysis for the detection of solid adulterants like cocoa shells in cocoa powder. Data recorded in the range of 1100–2500 nm was acquired for all samples to perform detection as well as quantification analysis. The classification analysis performed by using PCA and partial least squares (PLS) discriminant analysis (PLS-DA) and regression analysis showed high accuracy [54].

Spectral data of milk obtained from a single and three detectors UV-Vis and FT-NIR spectrophotometers were used for classification based on the geographical origin of the sample. The study proposes to develop a spectral-based classification tool to avoid adulteration in milk using Artificial Neural Network (ANN). Due to the higher dimensionality of the data obtained from the 63 samples of cow milk, PCA was used to check if clusters were formed among different groups. The principal components were then used as inputs for the Feed-forward Multilayer Perceptron ANN (MLP-ANN). The best fit showed accuracy of 100% classification irrespective of the type of spectrophotometers [55]. A few years back, the classification model for distinguishing tea varieties from visible and NIR spectra in the range of 325-1075 nm was reliable with an accuracy rate of 100%. The technique involves feature extraction by wavelet transform method, dimensionality reduction using PCA, and finally, BP ANN using 8 PCs as inputs [56].

Generating artificial outliers in ensemble decision tree classifiers like Random Forest proved to be a better model than PLS-DA for segregating the data obtained from ATR-FTIR and NIR of adulterated and unadulterated samples. The spectra-based non-destructive technique combined with ML models proved to be a less time-consuming method [57].

Spectral angle measure (SAM), Spectral correlation measure (SCM), and Euclidean distance measure (EDM) are some metrics that can be used for distinguishing minute differences in spectral values. One such report is that those metrics models were applied to NIR data for melamine adulteration in milk. These methods of SAM, SCM, and EDM showed almost the same performances in terms of accuracy on melamine screening from milk powders thus, proving NIR hyperspectral imaging technique and spectral similarity analyses as an effective way to detect melamine adulteration in milk powders [58].

Maturity index of mango was predicted based on NIR spectra in the wavelength range of 1200–2200 nm, collected from 1180 mangoes from various states of India. Multiple-linear regression (MLR) and partial least square (PLS) models were developed to predict the maturity index. A very good predictive PLS model was reported which uses the MSC data treatment in the wavelength range of 1600–1800 nm. Multiple correlation coefficients (R) for calibration and validation of PLS model were 0.74 and 0.68, respectively. Lower difference in standard errors of calibration (0.305) and prediction (0.335), indicated the potential of NIRS in non-destructive prediction of fruit maturity. [59]

Work had been done on the classification of food powders with open set using a portable spectrometer with frequencies in the range of 450 to 1000 nm. In the research, it had classified indistinguishable eight food powders with CNN (Convolutional Neural Network) that hardly caught the naked eye. Their experimental results demonstrated the capability of powder analysis using a portable spectrometer with statistical techniques of ML as a tool [60].

The convenience and feasibility of a similar technique like NIR i.e., hyperspectral imaging was studied for the detection of adulteration in prawns by subjecting the spectra data to Least-squares support vector machines (LS-SVM) for calibrating the gelatin percentage of prawn samples with their respective spectral data. For optimizing the wavelengths in the hyperspectral image analysis, the hybrid of Uninformative variable elimination (UVE) and successive projections algorithm (SPA) was applied to select the optimal values. The UVE–SPA–LS-SVM model gave quiet accuracy with a coefficient of determination (R^2) of 0.965, thus showing it to be an efficient tool [61].

SVM and PLS-DA were applied on visible-NIR hyperspectral data to check the feasibility of a handheld NIR sensor for identifying cultivars of barley, chickpea, and sorghum of Ethiopian variety. The ML algorithms delivered an accuracy of 89%, 96%, and 87% for barley, chickpea, and sorghum respectively [62].

A recent study aims to show the potential use of a commercialized spectrophotometer for determining the damage level caused by *Sunn Pest* insects. The spectral range was (400–813 nm) for Visible and for NIR wavelength range was 950–1636 nm. The calibration models based on PLS were found to be more accurate for higher damage percentages with an R^2 value of 0.89 [63].

Sprouted mung beans are generally preferred these days for their health benefits. Germination and sprouting depend on the metabolic energy status. The metabolic changes during the development of mung beans under different energy statuses were investigated by obtaining the Nuclear Magnetic Resonance Spectra. PCA of the spectral data showed the formation of clusters among the elements of the same groups and the supervised data analysis tool orthogonal partial least squares- discriminant analysis OPLS-DA showed a fit close to 1 [64].

Portable NIR sensors in the range of 740-1070 nm, that can be connected to smartphones showed a rapid and nondestructive way for on-site evaluation of fruits and vegetables using ML models [65].

PLS with second derivative preprocessing was found to be quite reliable for evaluating the concentration of glucose, fructose, and sucrose from NIR spectra of bayberry juice [66]. Similarly, FT-NIR-based data for evaluating glucose and fructose percentage in lotus powder was done using calibration models constituted by interval PLS of forward (FiPLS) and backward (BiPLS), PLS regression (PLSR), back propagation-ANN (BP-ANN) and least squares-SVM (LS-SVM) [67].

Hyperspectral imaging data combined with textural measurements obtained from salted pork were calibrated against pH values. thirteen important features were selected using PCA that were later processed by the PLS regression method. Predictability was better with an R^2 of 0.794 for the test samples based on data fusion (spectra and texture), making it superior to the results based on other data alone. Thus, providing a statement that methods of data fusion of spectral and texture analyses give more robust prediction [68].

To investigate the quality of oil, total polar compounds (TPC), free fatty acid (FFA), and conjugated dienoic acid (CDA) are generally measured. A rapid determination method for quantification of TPC, FFA, and CDA was developed by obtaining the Vis-NIR spectra in the range of 350 – 1050 nm. The spectra were processed using PLS and leave one out cross-validation that showed an accuracy in context coefficient of determination, R^2 of 0.984 for TPC, 0.973 for FFA, and 0.902 for CDA [69].

Eggs are generally stored at room temperature. During storage, they undergo certain changes like thinning of albumen, weakening of the vitelline membrane, and an increase in the water content. Predicting these changes with respect to the storage period is critical to monitor the egg's freshness. It has been proposed that PLS and ANN models can be used to determine the egg storage time using a low-cost portable NIR spectrophotometer [70]. In similar work related to the storage time of pork and its spoilage, instead of regression, classification algorithms like LDA, k-NN, and SVM were used taking the principal components of the spectra as inputs [71]. MATLAB also provides us with a PLS Toolbox that can perform multivariate analysis. Freshness in cheese is a very important factor. A MATLAB program based on principal component regression was developed that could predict the critical day of storage i.e. shelf life of cheese by acquiring FT-NIR and FT-IR spectra [72].

2.4 NIR based PAT

NIR technology is popular for its nondestructive nature. Also, NIR spectra are quite reliable predictors of changes occurring at the molecular level. Since drying involves changes in water molecules, NIR-based measurements can work well for predicting water content or water loss with respect to drying. There is a much need for an online quality prediction system. In simpler terms, the PAT system for ongoing moisture measurement during the process of drying for better quality after products. Since, NIR techniques are not specific in nature, apart from moisture content other quality parameters can be measured [73].

NIRS has shown to have a major scope in the food industry for its efficiency in process monitoring. It helps us in modeling a process by providing real-time analysis solutions [73].

Since fermentation is a complex process the process variables need to accurately be measured for delivering high-standard products. Grassi et al. [74] used multivariate curve resolution-alternating least squares (MCR-ALS) for mapping FT-NIR spectra, pH, and rheometric data with concentration at different stages of fermentation. The accuracy in terms of explained variance was around 99.9% and the lack of fit was 0.63665%. Another study quite elaborately explained how the based method helped in estimating the change in lactic acid fermentation with viscosity as reference data. NIR measurements were not only reproducible but also helped in quantifying the changes in the dynamic process of fermentation [75]. The alcoholic beverage industry also has a massive scope for NIR techniques. It has been used to study the factors affecting the fermentation process in beer [76]. Based on the polyphenolic profile, Spanish wines were distinguished using LDA, SIMCA, and SVM as ML tools [77].

NIRS has also been considered as a tool for non-contact interaction tool that helps in predicting the core temperature in liver pate during baking. Spectra acquired were in the range of 760-1250 nm and modeled using PLS [78]. NIR spectroscopy with an application of chemometrics has been regarded as a feasible method for online monitoring of meat [79]. The calibrated PLS model which was pre-processed using standard normal variate was quite successful in determining the core temperature of fish during heating using NIR spectra [80]. Mark et al. [81] developed a continuous near-infrared spectroscopic (NIRS) measuring tool attached to a fluidized bed drier that had been implemented to gain all essential product information rapidly and simultaneously for online monitoring of the drying progress and finding of the desired drying endpoint. NIR spectroscopy was used to develop a quick and robust quality control system for an active pharmaceutical ingredient to support the information obtained through PAT monitoring of its manufacturing process. Collell et al. [82] used NIR technology for online determination of superficial a_w and moisture content during the drying process of fermented sausages. A few examples like an NIR interference system for non-contact monitoring of the temperature profile of baked liver pate during baking, moisture content was also measured by near-infrared spectroscopy during storage of microwave-dried Yerba mate leaves, artificial intelligence-based systems for prediction of hydration characteristics of wheat and so on. A company named ‘Freund Vector uses NIR for drying technology and PAT for moisture estimation [83].

2.5 ML techniques for predictive modeling

ML and artificial intelligence are trending topics in today’s technological world. Be it in the banking sector [84] or medicine [85], it has found enormous potential in several fields. In the field of bioinformatics, ML upholds a tremendous role in genomics, proteomics, system biology, and text mining [86]. ML application has been widely growing in management sciences for data mining [87]. An article published in (https://medium.com/app-affairs) site discusses briefly about the application of ML in our day-to-day life activities e.g. Virtual assistant (popularly known as Siri, Alexa, and Google Assistant), Video surveillance, Social media services, Search engine results, Online shopping systems and so on.

It would be wrong to assume that in food analysis, ML techniques are only used for spectra calibration. There are other applications e.g., a multivariate analysis-based classification tool for predicting the cooking qualities of different rice ideotypes was proposed to be a convenient way of estimating cooking and eating quality making it useful for consumer preferences for further analysis. The data that were taken into consideration were viscosity, rheometric, and mechanical texture parameters [88]. Deep learning models like CNN form weight sharing architecture for visual data, RNN feedback recurrent for time series data and LSTM handles lags for time series data have proved to be highly reliable methods for sequence learning, recognition of visual data, and sub-division tasks to classify plant and for understanding physiology by using images of the plants [89].

We can describe machine learning as a part of artificial intelligence that learns from data and enables the computer to perform different tasks based on data. It is different from conventional programming where we define the method and get output; it is rather generating the method from the output (data). The property of the data points is called features [90]. ML process involves the methods shown in Fig. 1 [91]:

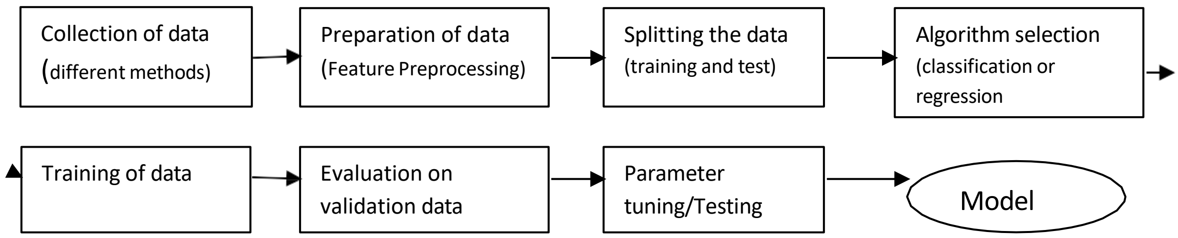

Fig. 2.1: Steps involved in ML

The different classes and subclasses of ML that can be used as **calibration** models are briefly discussed in Table 2.1. We can broadly classify ML techniques into supervised, unsupervised, and reinforcement learning. Supervised learning is for data that are labeled or whose outcome is known whereas unsupervised learning is for unlabeled data. Reinforcement learning allows acting based on a situation from data that are not predefined. Neural networks and deep learning are closely related to each other.

ML techniques also provide us with statistical metrics to evaluate the execution of calibration models. The **validation** methods are briefly discussed in Table 2.2. Based on these parameters we can decide which the best calibration model is and how accurately it predicts the output with minimum error. It tells about the efficiency of the model.

Table 2.1: Types of ML and their respective models

Types of learning	Techniques	Models	References
Supervised	Regression	Simple regression	[92]
		Partial least square	[93]
		Ridge regression	[94]
		Lasso regression	[95]
		KNN regression	[95]
		Kernel regression	[96]
	Classification	Linear classifiers	[97]
		Logistic classifiers	[98]
		Decision trees	[99]
		Random Forest	[100]
		Naïve bayes	[99]
		Linear discriminant analysis	[101]
		Support Vector machine	[101]
Unsupervised	Dimensionality reduction	Principal component analysis	[102]
		Factor analysis	[103]
	Clustering	K Means clustering	[104]
		Hierarchical clustering	[104]
Reinforcement	Trial and Error	Monte Carlo	[105]
		Q learning	[106]
		State-action-reward-state-action	[107]

Table 2.2: Statistical metrics for performance evaluation

Statistical term	Symbol used	Description
Coefficient of determination	R^2	It is described as the proportion of variance between the actual and predicted measurements.
Euclidean distance	D	The perpendicular distance between two coordinates.
Manhattan distance	|D|	It is the actual distance between two points measured along the axis.
Classification Accuracy	CA	Ratio of accurately predicted units to total units.
Precision	P	The ratio of True Positive (TP) to the sum of TP and False Positive (FP).
Recall	R	True Positive (TP)/True Positive (TP)+ False Negative (FN)
F1 score	F1	Harmonic mean of Precision and Recall.
Mean Square Error	MSE	Average of the squared of errors (difference between estimated and predicted.
Root Mean Squared Error	RMSE	Standard deviation between the estimated and predicted value
Mean Relative Error	MRE	Mean error values between predicted and estimated.
Maximum Likelihood Estimation	MLE	Estimating the parameters of a probability distribution function that gives maximized value.

There are several reports on how ML supports NIRS. There are several literatures reporting the applicability of ML and spectroscopy in adulteration, identification, proximate evaluation, storage quality, process monitoring, and post-harvest analysis. The most widely used ML techniques are PCA, PLS, soft independent modeling class analogy (SIMCA), k- k-nearest neighbor, classification and regression tree, support vector machine, and random forest classifiers [78]. In this review, we are mainly focusing on the recent application of NIR and ML for food quality evaluation and process monitoring.

It started in the year 1960 with the access of computers to scientists and at that time the NASA Mars mission required chemists to perform structural elucidation. Later, in the 1970s analytical chemistry merged with multivariate techniques and statistics. The term 'Chemometrics' was first used in the year 1972 which was earlier known as chemical pattern recognition. NIR calibration was one of the primary uses of these techniques. Later, with the advancement of science and technology, these techniques found a broad range of applications in the medical sciences and food chemistry sector. This is how the applications of ML techniques have emerged [108]. Chemometrics is another nomenclature for ML that involves multivariate analysis to extract information from chemical data. It involves the use of mathematics, statistics, and computation to select optimal procedures for chemical experiments. It is generally a process of multi-calibration of the chemical data to get a cause-effect relation with the analyzed parameters. One can't deny the scope of chemometrics in the field of NIR spectroscopy. NIR spectroscopy, being a secondary technique, requires chemometrics for calibration purposes. Chemometrics methods have also been present as an alternative to chromatography [109]. Gatlier and co-researchers [110] used chemometric techniques to extract chemical information from spectral data of virgin olive oil. NIR spectroscopy combined with chemometric techniques was successful in differentiating powder from different brands available in the market [111].

2.6 Portable spectra based sensors

At present times, there are advancements in the technologies for instrumentation and it has resulted in the manufacturing of portable spectrophotometers that can give spectral data without time consumption making it better for rapid analysis [53]. It uses ML as a calibration tool to map a link of near-infrared spectroscopy-based measurements into desirable extrinsic factors of analysis for quality that uses our smart-phone as a visualizing medium for output.

In this study, we plan to briefly discuss such applications of ML as an enabler for calibration and validation tools of NIR spectroscopy. This will surely give us insight into how we can apply ML techniques combined with NIR to provide better solutions to the food industry in quality analysis and as in process monitoring.

The most used ML model for spectral data in food analysis is PLS followed by PCA. Additionally, the availability of Open-Source Programming languages like Python and R, has made the task quite accessible for all. Thus, we can say that the ML technique in combination with NIRS; can be extended in the field of food technology to provide better solutions in the food industry.

2.6.1 Advantages of portable sensors for analysis purpose

Portable devices with prior calibration using ML models can be a great boon for the purpose of analysis due to the various reasons such as (i) rapid analysis (ii) on-site evaluation (iii) reagent-free technology (iv) cost-effective compared to bench-top equipment (v) useful for measuring parameters that are not time-stable (vi) utilizable for a wide range of analysis (vii) applicable for PAT systems [112]. There are a reported works of literature available that have worked on portable spectrophotometers for analysis purposes. A few are briefly cited in Table 2.3 (Page 29).

2.7 Recent works in the similar field

Recently, researchers from the Hamburg School of Food Science, Germany have published a work regarding identification of the demographically different white asparagus using FT-NIR and chemometric techniques. Thus, demonstrating the ability of NIR spectroscopy combined with ML methods as a separating tool for accurate screening of asparagus [123].

Researchers at IARI, India has used ATR–FTIR for the detection of skim milk (SM) adulteration. In this study, milk adulterated with known quantity of SM were acquired in the wave number range of 4000–500 cm^{-1} using Attenuated Total Reflectance (ATR)–FTIR. The acquired spectra revealed differences amongst milk, SM and adulterated milk (AM) samples in the wave number range of 1680–1058 cm^{-1}. This region encompasses the absorption frequency of amide-I, amide-II, amide-III, beta-sheet protein, α-tocopherol and Soybean Kunitz Trypsin Inhibitor. Principal component analysis (PCA) was used for clustering of samples based on SM concentration at 5% level of significance. [124]

Table 2.3: Details about the available portable NIR sensors used in Agriculture

Sl.no.	Application/Study	Type/Manufacturer of sensors	Wavelength (nm)	Reference
1	Comparison on the performance of three hand handled device for Umbu fruit quality parameters	Sensor for raw produce quality meter named F-750 (Felix Instruments, Portland, USA) Tellspec (Tellspec Inc., Toronto, Canada) Scio Version 1.2 (Consumer physics, Israel)	300-1150 900-1700 740-1100	[113]
2	Prediction of postharvest dry matter and soluble solid content	Sensor named F-750 for raw produce quality meter (Felix Instruments, Portland, USA)	310-1100	[114]
3	Segregation of seedlings for postharvest fruit phenotypes	NIRvana (Integrated Spectronics, Australia)	400-1100	[115]
4	Prediction of Kiwi Fruit dry matter after postharvest using optimized six wavelengths	NIRvana (Integrated Spectronics, Australia)	300-1150	[116]
5	Assessment of internal flesh browning in apples	Three different halogen lamps as source 30 W, 150 W and 300 W	302-1150	[117]
6	On site measuring nitrogen content and mass per unit area of leaf of wheat in throughout plant cycle	Spectralon (Labsphere Inc., New Hampshire)	250-2500	[118]
7	Non-destructive way of measuring fruit maturity using Vis-NIR spectrophotometer	Hamamatsu S 3904 256Q (Lab developed set up)	310-1100	[119]
8	Physical and chemical assessment of mandarin during harvest using NIR spectrophotometer	Phazir 2400 MEMS Instrument (Polychromix Incorporated Companies, Wilmington, USA)	1600-2400	[120]
9	Detection of allergens in food using smartphone	Tellspec food Sensor (Tellspec companies, Toronto, Canada)	1350-2150	[121]
10	Consumer scale NIR sensors for kiwifruit quality measurement	Tellspec food sensor (Tellspec companies, Toronto, Canada) Scio Version 1.2 (Consumer physics, Israel) LinkSquare (Stratio Inc., Seoul, Korea)	1350-2150 740-1100 400-1100	[122]

Machine vision has been been used for the quality inspection of food and agricultural produces, as reviewed in the work of Patel et al [125]. Conventional machine vision just assigns the primary colors (RGB) to each pixel. However, Hyperspectral imaging (HSI) is different from conventional imaging as it uses a wide range spectrum of light and assigns spectral values to each pixel, thereby adds a third dimension to the two-dimensional spectral data

The main advantage of hyperspectral imaging (HIS) systems is the ability to integrate both the benefits of spectroscopy and imaging techniques to evaluate different components directly at the same time, as well as localize the spatial distribution of such components within the tested product. HSI is better compared to NIR spectroscopy for generating more accurate and detailed information. This makes it very appropriate for the application of HSI in food and agro-sectors, where certain targeted regions need to be specified.

In hyperspectral data, the spectral range can extend beyond the UV-visible range to the Infrared range. Now, the advancement of technology and different data handling software being made so easily available has given opportunities for creating viable and efficient solutions, be it military or agriculture. HSI application has made promising progress in the field of analytical technology [126]. Here, the application of ML, a type of artificial intelligence, plays a big role in mapping the data.

Recent applications:

Poultry: The poultry industry has the potential application of HSI. Hyperspectral imaging application has been found to be a useful technique for detecting egg freshness, scattered egg yolks, and cracks [127]. Another critical demand is non-invasive early in-ovo chicken sexing methods to avoid the culling of eggs. On-line inspection of chicken breasts to find wooden breasts using HSI is a non-destructive application saving much time.

Cereals: HSI has a big capability for grain inspection, evaluation, and control of bulk storage. Particularly, hyperspectral imaging systems utilizing line or area scanning were considered capable and proposed for application in bulk grain storage quality inspection. Existing literature shows that most studies on the application of hyperspectral imaging for grain quality assessment were majorly focused on wheat. Future research should consider other grains [128]. Hyperspectral imaging is a viable technology for heterogeneous contamination control in grains by identifying mycotoxin levels, and HSI is a suitable technique for fungal-damaged kernel detection at industry entrance [129].

Fruits and vegetables: Gingerols and gingerol derivatives are the major bioactive chemicals in ginger that are responsible for its pungent flavor and bioactive characteristics. To determine the ratio of both compounds, a hyperspectral method works well [130]. NIR- HSI Imaging makes it possible to track the concentration of nutrient components in Textured Vegetable Protein quality control that can be done with the help of chemometrics [131]. The non-destructive analytical nature of HSI makes it very appropriate for online investigation of fruit quality during processing, for example, jujubes, apples, strawberries, etc. [132, 133].

Milk: Although for milk, there are a few rapid biochemical processes available. While, for complex processes, HSI is a boon to milk industries [134]. For example: point-scan Raman hyperspectral imaging technology for rapid detection of non-protein nitrogen adulterants in milk powder, rapid identification of *Escherichia coli O157:H7* and *Listeria monocytogenes* in dairy products, etc. [135].

Sensory: Traditional sensory property analysis methods, such as trained sensory panels, colorimeters, and texture analyzers, are invasive, time-consuming, and small-scale operations. HSI has evolved as a less time-consuming and non-destructive way of determining the sensory qualities of a wide variety of foods [136].

2.8 Summary of Chapter II

The literature review of the work discussed the processing of rice and how different parboiling methods have benefitted in terms of quality improvement as well as improvement of energy efficiency. Parboiling of *Chokuwa* rice grown in the state of Assam, which is a low amylose variety manufactures *Komal Chaul* which has a distinctive characteristic of ready to eat by soaking it in warm water. The previous work done on *Komal Chaul* focuses on its nutritional information and standardization of the process for enhancing the quality as well as process efficiency. Ageing due to various factors only happens in rice as a cereal, and many works had been done earlier to study at the physicochemical and molecular level. However, there has been no literature found on the ageing process of *Komal Chaul*. A detailed study on nondestructive techniques like NIRS gave us information about the application of this technology in food assessment and the preference of its application for various process analytical purposes. And advancement of ML models and their integrability to sensors have provided real-time solution.

2.9 References to Chapter II

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