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Predictive AI Models for Food Spoilage and Shelf-Life Estimation

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ABSTRACT

Food spoilage is a global problem which causes food waste, economic loss and foodborne illness. The shelf life and spoilage estimation of food is traditionally done with fixed expiration dates and this leads to disposal of still eatable food or eating spoiled food. Recently, with the development of the Artificial Intelligence (AI), the predictive models have been developed to better evaluate the food spoilage based on such factors as temperature, humidity, microbial activities and gas emissions. This paper discusses the part played by AI in the prediction of food spoilage, while also outlining various machine learning and deep learning models (regression, classification, convolutional neural network – CNN and hybrid AI). Food spoilage estimation powered by AI relies on multiple sources of data including IoT enabled sensors, Spectroscopy as well as real time environmental monitoring. The practical use in the food industry of such data driven models is in the context of real life applications as smart packaging, AI powered quality in supply chains, retail inventory product optimization. However, the adoption of AI in this field is limited as the data is scarce and of low quality, the models have limited accuracy, ethical concerns exist, and implementation is expensive. In this review, potential for AI in transforming food spoilage estimation is highlighted and this could be achieved by working on obtaining greater accuracy, scalability, and adoption of the model in different food sectors. The role of AI in enhancing food security, sustainability and efficient use of resources, waste reduction and increasing accessibility of good quality perishables to every consumer will gain increasing feasibility with the improvement in AI.

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INTRODUCTION

Food spoilage poses a major challenge to the global food industry, resulting in huge economic losses, food waste, and possible human health risks [1]. Knowing exactly when the food will spoil prevents spoilage, minimizes waste and improves the food's safety and inventory management. Methods of shelf life determination using chemical analysis, microbial testing, and sensory evaluation are time consuming, costly, and usually involve destructive testing methods. Therefore, there is an expanding need for novel, data-driven ways of estimating food shelf life and predicting food spoilage in a more efficient manner. Just as in food production, artificial intelligence (AI) is an emerging technology in food science that promises to significantly improve estimation of the food shelf life and increase its accuracy and efficiency [2]. Food scientists and manufacturers can use those models, which leverage AI, to analyze huge flows of different kinds of data, including temperature, humidity, packaging conditions and how food microorganisms grow, and make very precise predictions on when food spoils. These methods use machine learning (ML), and deep learning (DL) techniques for spoilage trends detection, food freshness level classification and real time alert for risks [3].

Several advantages stem from the integration of AI in food spoilage prediction. Secondly, the AI models use large data sets much faster than traditional methods, making it possible to provide real-time decisions. Secondly, predictive AI models increase the reliability in spoilage estimation by discovering relations that might not be explicit from manual insights. Additionally, AI powered monitoring systems offer dynamic shelf life estimation which is adjusted based on real world storage conditions rather than static expiration dates [4]. This dynamic approach diminishes the amount of food wasted by prolonging the time for these products to be utilized before spoiling and improves the safety of the food chain by increasing the time available to identify spoilage risks. Besides, the AIbased food spoilage prediction systems are increasingly integrated into the smart packaging solutions [5]. These IoT enabled sensors continuously monitor the storage conditions and keep feeding the data to AI algorithms, which algorithms assesses the quality of the product. Meanwhile, consumers are able to access more real time info about the food's freshness via mobile apps or smart labels so that they can decide on consumption accordingly.

Although AI food spoilage estimation has its many advantages, some challenges still need to be overcome in its adoption, which include need for high quality training data, the complexity of food spoilage mechanisms and regulatory compliance issues. Although AI technologies are continuous evolving across the world and integrated with the Internet of Things (IoT), block chain solutions, they

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have the capabilities of transforming the way food safety and quality are being managed in the supply chain [6]. In this review article, different AI models used for food spoilage prediction, their data source, applications, limitations, and trends of the future will be reviewed. The following sections look in depth at how AI is influencing the future of food safety and waste management.

UNDERSTANDING FOOD SPOILAGE AND SHELF-LIFE

The natural process of food deterioration and quality deterioration to unsafe or undesirable conditions for consumption. The factors are biological, biological and physical, which induce changes in the food's taste, texture, color and nutritive value. These factors need to be understood in order to be able to estimate the shelf life of different food products and put some strategies in place to extend the preservation of the food. [7] Bacteria, molds and yeasts are the most common cause of food spoilage, and all are perfect examples of molds, you can find molds in your cupboards, and mold among your grocery products. The breakdown of food components by the microorganisms lead to off flavors, odors and harmful toxins. For instance, Bacteria that result in spoilage and which are harmful to human beings are: Listeria, Salmonella, and Escherichia coli [8].

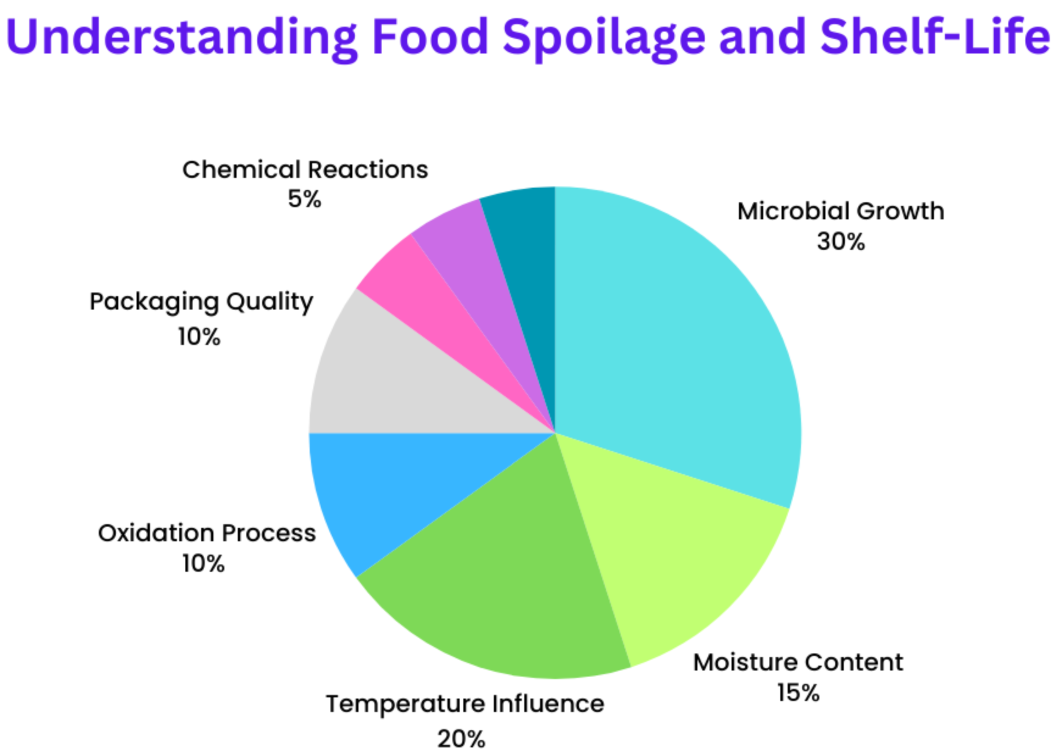

Figure: 1 showing understanding of food spoilage and shelf life

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Also, food stuffs continue to react with the natural enzymes in food stuffs after harvest or processing hence undesirable changes. Thus, fruits and vegetables are enzymatically browning, dairy products protein break downing, and thus affecting the taste and texture. Food spoilage is largely due to oxidation. The presence of free radicals in fatty foods like oils, nuts, and meat result in rancidity which impinges on flavor and nutritional value [9]. Food quality is adversely influenced by other chemical changes such as protein denaturation and vitamin degradation. Food spoilage is greatly affected by temperature, humidity, light exposure and availability of oxygen. In high temperature, microbial growth and enzymatic reactions are accelerated, while in excessive humidity, mold is formed. Sensitive nutrients such as the vitamins A and C can be degraded upon exposure to light [10].

Food products' shelf life is determined by the type of packaging used. Vacuum sealing, modified atmosphere packaging (MAP) wherein the gas atmosphere around the food is replaced with a controlled atmosphere, and active packaging, such as in packaging with oxygen absorbers, are methods that help lengthen shelf-life by controlling the growth of microbes and oxidation. Proper food storage conditions like fluctuation in temperature during transportation can reduce the longevity of food. Presence of spoilage causing bacteria and fungi are determined through laboratory based microbial analysis. The methods of standard plate count techniques are used to predict shelf life based on acceptable safety limits [11].

The indicators of spoilage such as changes in pH, lipid oxidation level, and volatile compound formation are measured by chemical tests. As for example oil peroxide value is measured to find out the level of rancidity. Food spoilage is measured based on human perception in sensory tests. To know that food is still good to eat, experts look at changes in the food's color, texture, aroma, and taste. Unfortunately, this method is not an objective method and is not suitable for large scale applications. Estimation of shelf-life using traditional predictive models such Arrhenius equation and microbial growth models [12] is based on the knowledge of the prevailing environmental conditions. However, these models give a theoretical estimation of storage conditions and do not always give a high number of accuracy for dynamic storage. Although they offer valuable insight, traditional methods are limited in that they are time consuming to process, expensive, and inaccurate under conditions of changing storage conditions. These AI based predictive models are well suited to be a more efficient solution for shelf life estimation. These models take into account data from various sources including sensor readings, microbial database information, and historic spoilage trends that can increase their accuracy and allow for real time decision making [13].

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ROLE OF AI IN FOOD SPOILAGE PREDICTION

Intervention in the field of food spoilage prediction by Artificial Intelligence (AI) is changing the face of the food industry for which it makes sure there is quality, safety and sustainability. At present, predicting food spoilage is based on microbial testing, chemical analysis and sensory evaluation, which are often time-consuming, costly and susceptible to human error. In contrast, AI driven predictive models provide more accurate, real time, and data driven approaches to establish shelf life along with spoiling risks [14]. Large datasets of all types, such as temperature logs, humidity level, gas composition, microbial growth are used to train AI models to predict food spoilage with near perfect precision. The thousands of lines of data collected from SDAs are analyzed by machine learning (ML) and deep learning (DL) algorithms which are capable of recognizing these spoilage trends and giving the industry actionable insights. It gives food manufacturers, retailers and consumers the chance to make educated decisions and this will go a long way for easing food waste and food safety [15]. There are a variety of machine learning techniques used by AI based predictive models for food spoilage:

The algorithms are trained on labeled datasets of datasets with spoilage related information of possible microbial growth and environmental conditions. They can then take new input data and be able to classify food products as fresh or spoiled. [16] In case of the lack of pre landmarks in food quality datasets, AI models are able to discover hidden trends therein. It is useful for spotting anomalies of food spoilage, like unexpected microbial activity, gas emissions and so on. Example: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) – based advanced neural networks, analyze the image data (e.g., mold found on fruits) and time series data (e.g., spoiled fruits over time prediction). The combination of machine learning and deep learning techniques utilizing multiple data sources such as sensor data, historical trend, and real time monitoring system improves the accuracy of spoilage prediction [17].

In processing sensors data continuously, businesses can use AI models to detect spoilage as early signs and prevent it from happening by adjusting the storage conditions. Unlike traditional methods, which solve a specific problem, the AI models take into consideration a large number of variables together, resulting in more accurate and a reliable predictions of spoilage. Instead of static expiration dates, AI can supply a real time shelf life which is dependent on the specific storage conditions and help avoid waste of inessential food. Manual testing is redundant in case of AI powered systems resulting in lowering of operational costs and improving efficiency of food quality control [18]. AI

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predictions of food spoilage before it's visibly there help keep a consumer away from foodborne illnesses and help companies comply with food safety regulations. With this advancement of AI, it will be expected to couple with Internet of Things (IoT) sensors, block chain for food traceability, and cloud based analytics for global food supply chain optimization. There is also traction to the AI driven smart packaging that gives a real time spoilage alert through mobile apps [19].

TYPES OF AI MODELS USED IN FOOD SPOILAGE PREDICTION

Food spoilage prediction with the help of the AI is based on very sophisticated, high computational models that process the big data and provide the answer on shelf life and the possibility of the spoilage risk. Depending on food product type, accessing data and accuracy need, we use different AI models. Traditional machine learning algorithms, deep learning and hybrid AI models are ubiquitous, they range from traditional machine learning algorithms to deep learning and hybrid AI models which have their own specialties in the areas of spoilage pattern recognition [20]. The prediction of food spoilage is widely applied in ML models, because of its capability to process structured and unstructured data. These models, including, linear regression and multiple regression, are some common ML models which analyze historical data for prediction of expected shelf life of the food product based on temperature, humidity and microbial growth rate [21].

These models are used to classify food items as to whether they are fresh, near expiration, or in the spoilage state. However Random Forests is an algorithm that combines many decision trees to increase accuracy. SVMs are used to analyze the results of image or chemical composition datasets for classifying (classifying) the freshness of the food or how long it took the food to spoil. The Deep Learning (DL) models are advanced form of ML techniques that can process large set of complex data like images, time series sensor data, SI chemical compositions and so on. To spot visual signs of spoilage of food products such as mold growth, discoloration or texture changes, CNNs examine images of the products. Automated food inspection systems commonly use such systems [22]. These models prove useful to process time series data collected from IoT sensors monitoring temperature, gas composition, humidity etc. in food storage environments. The spoilage progress over time is predicted. [23] Generates synthetic data using GANs to simulate different spoilage conditions, in order to enhance the prediction accuracy of cases where data from real world is limited.

To improve the accuracy of the prediction, the hybrid AI models combine different machine learning and deep learning techniques. For instance, Smart sensors monitor and collect real time data regarding

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food storage conditions and process the collected information by ML/DL models in order to generate instant spoilage alerts. Uses a combination of different AI models (i.e. random forests combined with CNNs) to improve prediction reliability using multiple data sources. With the continuing refinement in the AI technology, the model will become more accurate, and can fit to various food category [24]. Posted with more AI integrated with IoT, block chain and cloud computing, the food safety and wastage reduction is going to improve further. The food industry will see further improvement by the use of AI driven predictive models to provide more accurate, data based spoilage trend and shelf life estimation [25].

DATA SOURCES FOR AI-BASED SPOILAGE PREDICTION

Close accuracy and effectiveness of the prediction depends on the quality and the diversity of data used for training as well as for real time monitoring. AI models are able to detect spoilage patterns and estimate shelf life by analyzing sensor based readings, image analysis, spectroscopy data and other environmental factors. These data sources can be integrated with each other, making the predictability of the predictive AI model more precise, and helps the food manufacturers, retailers and consumers make confident decisions [26]. Real time sensor based monitor is one of the most critical sources of data for AI models. Food packaging, storage units and the supply chain logistics are embedded with advanced sensors which collect data on key environmental parameters for spoilage. Some commonly used sensors include:

Help AI predict how temperature fluctuations affects food’s shelf life by measuring current storage conditions. Monitor the moisture levels that can cause microbial growth and degradation of the food. Signal spoilage in fruits and vegetables by detecting gases like ethylene, and in dairy and meat products by detecting carbon dioxide. Acidities can be measured in changes of perishable foods such as dairy, seafood, and beverages to show bacterial activity [27]. It involves detecting the presence of microbial metabolites or DNA sequences that would indicate specific bacterial contamination in food samples. These sensors are integrated with Internet of Things (IoT) technology which can constantly send the real time data to the cloud based AI platforms for predictive analytics and automated spoilage detection [28].

Another rich source of information for spoilage prediction use visual and spectral data. AI models leverage computer vision and spectroscopy to identify the early warnings of food spoilage, that are not detectable by the human eye [29], thanks to AI-powered image recognition models, such as from

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Convolutional Neural Networks (CNN) that detect changes in visual quality of food products which may include discoloration, mold growth, texture changes, etc. They may be used in automated quality control systems in food processing plants. These are very novel techniques in assessing the chemical composition of food, by virtue of the manner in which light interacts with different substances. Specular data are processed by AI models to detect early spoilage markers (protein degradation in meat, oxidation in oils, etc.) [30].

The AI models' spoilage prediction also depends on historical and current environmental data. However, not all aspects of food shelf life are controlled by manufacturers of food products, as several external factors contribute to this. Food degradation accelerated due to exposure to oxygen and AI models predicting spoilage risk in packaged food based on oxygen sensor data. AI uses data from light sensors to find out how much UV radiation damages nutrients in dairy, oils and beverages, for example. The predictive power of AI models in estimating food spoilage can be further improved if multiple data sources are combined [31]. AI can provide real time, dynamic and accurate shelf life predictions while integration of real time specification data, image and spectroscopy analysis and environmental conditions. With the advancement in AI technology, better spoilage detection and food safety management can be continued as data collection, whether biosensors or spectral imaging, improves. In the following sections, I am going to talk about food industry's use of AI models with special focus on the challenges of implementing AI-driven spoilage prediction systems [32].

APPLICATIONS OF AI IN THE FOOD INDUSTRY

Food industry is revolutionizing through use of Artificial Intelligence (AI) for improving food safety, reducing waste and enhancing quality control. The applications of AI powered predictive models for food spoilage and shelf life estimation span in several areas such as smart packaging, real time monitoring, supply chain management and retail. These applications assist food manufacturers and distributors as well as consumers to make the right call so that the food remains fresh and safe for consumption [33]. An AI innovation that is one of the most innovative uses of AI in food spoilage prediction to date is smart packaging, which incorporates sensors and AI analytics to measure food freshness in real time. Smart packaging technologies include:

Temperature, humidity and gas emission are tracked by embedded sensors inside the food packaging. To track spoilage risks and transmit real fresheness information, these sensors pass data to AI models. Time Temperature Indicators (TTIs) and pH-sensitive labels that turn color as food approaches

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spoilage allow consumers to be alerted. For example, AI driven freshness reports can be accessed by the consumer to view freshness by scanning QR codes on food packages which include real time sensor data and storage history [34]. In addition to saving labor costs, these innovations help cut down on food waste, reducing the static expiration dates that can be conservative and lead food that is still edible to be thrown away. In optimizing food supply chains, ensuring food quality from production to consumption, AI is always an important part since the process cannot be penetrated by conventional means, and humans cannot control it. Some key applications include:

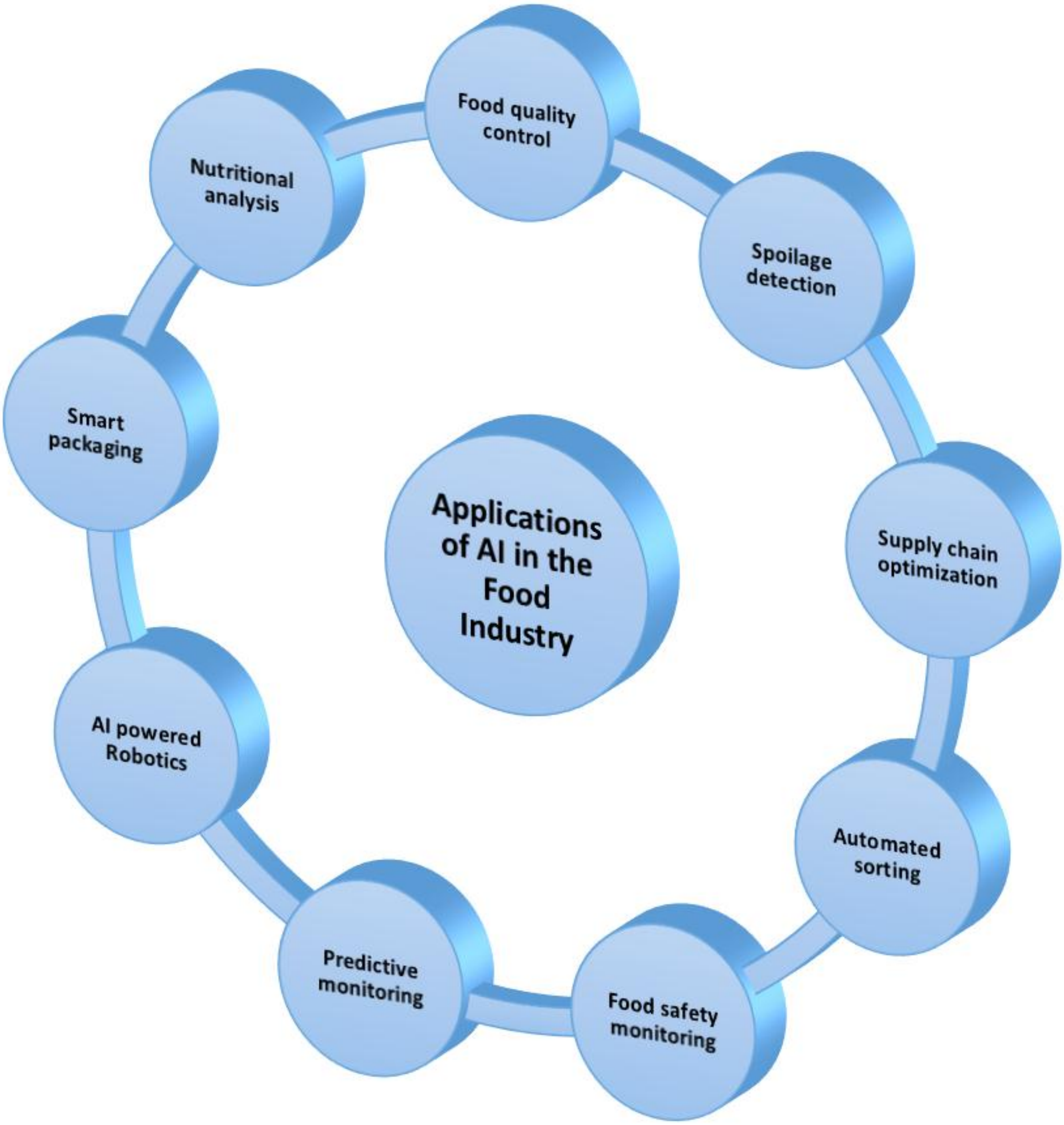

Figure: 2 showing applications of AI in food industry

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AI is used to look at storage conditions from warehouses and transportation units to predict the failure of equipment (such as refrigeration failure) that could lead spoilage. Computer vision systems powered by AI are used to evaluate the quality of fruits and vegetables, meat and seafood, by spotting physical defects, discoloration and contamination. It keeps high quality standards up and lowers the opportunity for consumers to receive spoiled food [35]. The combination of AI and block chain allows for transparent food supply chains where food is tracked from farm to table and where the potential contamination points in the event of a food spoilage led recall, can be easily identified. The AI applications which aid food purchasing and consumption decisions are beneficial to both retailers and consumers. For instance, grocery stores leverage AI to examine sales data to forecast customers' requirements and organize store restocking schedule to mitigate waste and preserve freshness of products [36].

AI applications recommend recipes and meal plans according to what food is near or needs to be eaten before spoiling. AI refrigerators are equipped with AI features that monitor the food items, track their expiry and send alerts to the users so the food items can be properly utilized reducing the food waste and increasing efficiency of household food management. [37] There is a great opportunity to apply AI in the food industry, which is changing the way food security, food quality control, and waste management is done. Smart packaging, real time monitoring, AI driven supply chain optimization and personalized consumer solutions are just some of the ways AI is improving efficiency throughout the entire food lifecycle. Given that AI technology is evolving, more innovations can be expected to assist in building a sustainable and waste free food ecosystem. We will now cover in the next sections the challenges and limitations to use AI models for food spoilage estimation [38].

CHALLENGES AND LIMITATIONS OF AI MODELS IN FOOD SPOILAGE ESTIMATION

Although AI has great potential for disrupting the food spoilage prediction and shelf life prediction space, there are some roadblocks that must be overcome before it can be used. The challenges cover from data-related ones to model accuracy, generalization, ethical and regulatory problems. These limits must be overcome for reliable and efficient AI driven food safety systems to be developed [39]. The success of AI models to predict food spoilage relies on large amount of high quality data. However, there are data related challenges such as food spoilage is affected by many variables such as food composition and storage conditions as well as microbial growth. However, [40] is a hard and inconsistent problem to gather extensive, high quality datasets of diverse food products.

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There are different methods used by different food manufacturers and retailers to capture the data related with spoilage. This absence of standardized data collection protocols compromises the training of AI models because it has an impact on the datasets used. In developing regions, there may not be a suitable technological infrastructure for BI implementation to collect and share the real time food storage and spoilage data [41]. This will enable attempts to create global data sharing platforms and standard datasets of food spoilage. The AI models need to be accurate and generalizable to different foods and storage conditions. But, a few challenges affect model performance.

There is a challenge that AI models trained on a certain set of environmental conditions, may not have ability to predict accurately when the spoilage happens on other regions or climates. For instance, a model trained with European storage conditions does not work in tropical conditions. [42] Some AI models may fit the training data very well but are not useful when presented with new conditions. On the other hand, models over fitting will lead to poor predictive performance because the patterns are too simplified. As new food preservation technologies become available, AI models need to be updated with respect to how food is stored and packaged in ways the model makes sense. Accuracy maintenance requires regular retraining with new data. Though adoption of AI in food spoilage estimation also involves ethical and regulatory concerns, like in case an AI wrongly predicts spoilage and results in food borne illness or food waste [43], it is difficult to determine responsibility.

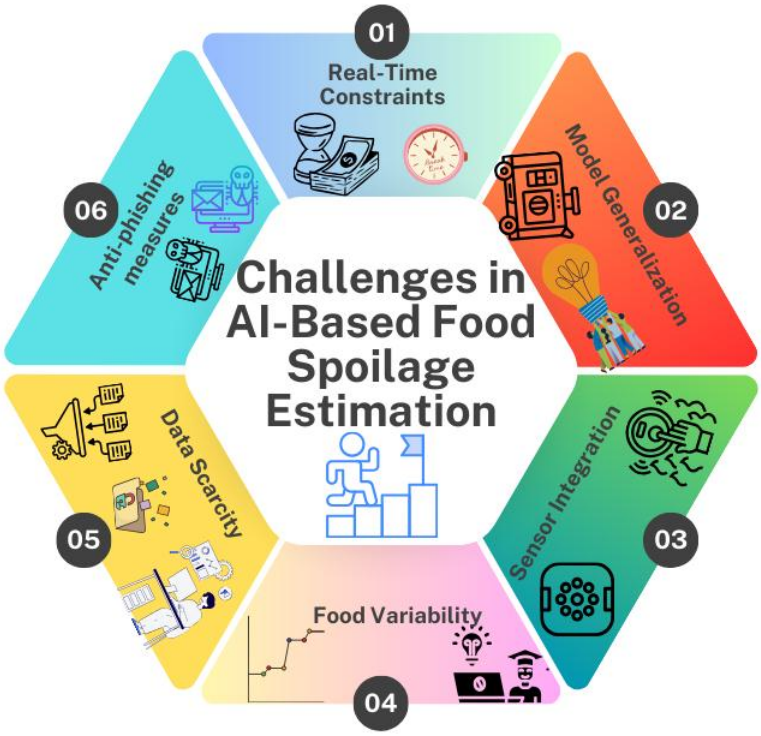

Figure: 3 showing challenges in AI based food spoilage estimation

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Consumers opt for traditional expiration dates rather than AI driven food quality assessments for there are many consumers who are skeptical about AI. To build trust, effective communication and transparency over what is being predicted and the potential limitations of a system are required. The food safety regulations vary from one country to the other. Wide use of AI models can be achieved only if they comply with international food safety standards and regulation. Training and real time analysis of such advanced AI models, especially deep learning approaches are needs a lot of computing resources [44].

Costly IoT enabled smart sensor for real time monitoring makes it hard for small scale food businesses to adopt AI solution. There are lots of food industry players whose legacy systems may not have the ability to communicate with AI driven spoilage prediction technologies, in which case, pay big money for system upgrade. Although AI offers great potential for food spoilage prediction and shelf life estimation, these must be met challenges, focusing on data availability, model accuracy, ethical aspects and high implementation costs [45]. To conclude, future research should target the improvement of AI model generalization, development of data sharing initiatives, and to the creation of low cost AI solutions to promote the use of predictive food spoilage models within the global food industry. The next section focuses on emerging trends and innovation that can help overcome these challenges and promote AI adoption in food safety.

FUTURE TRENDS AND INNOVATIONS IN AI FOR FOOD SPOILAGE PREDICTION

With the progression of Artificial Intelligence (AI), one can expect them to use food spoilage prediction and shelf life estimation in much sophisticated, accurate, and accessible ways. Recent trends in the development and integration of AI and IoT in food safety and waste reduction endeavors, block chain-based food traceability, and innovative uses of deep learning techniques are changing the landscape of food safety and waste reduction. The latter will be vital in improving food quality, minimizing supply chain inefficiencies and cutting down global food waste [46]. However, by only combining AI with the Internet of things (IoT) smart sensors real time monitoring of food spoilage can be done. The continuous data on temperature, humidity, gas emissions and microbial activity are these IoT enabled devices. So the data is processed instantaneously by AI algorithms and it predicts spoilage and notifies manufacturers, retailers, and consumers [47].

The future food packaging will include AI driven sensors that will use pH changes and gas emissions to assess freshness. This will bring static expiration dates to life through real time spoilage

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assessments. Real time spoilage detection will be enabled by AI models running on edge device (local processors in warehouses or retail stores) bypassing cloud based computation thereby minimizing latency while increasing their ability to make decisions. Block chain technology is one that can be used to improve food safety and ensure transparency and to remove food fraud [48]. By recording each stage of food production, storage and transportation, block chain allows for the data of spoilage to be immutable and verifiable. With the help of AI, block chain data can be analyzed to extract patterns of risk of spoilage in supply chain [49], so that stakeholders have a chance to act beforehand when food is at unsafe state.

The proposed idea is to connect the food packaging with the block chain, enabling consumers to scan the QR code on the packaging and get freshness reports verified by block chain. With more research on AI, the more sophisticated deep learning techniques will make spoilage prediction better. • Future AI models will be continuously learning from new information—and as more is learned they will adapt to predict spoilage across food categories and under different environmental conditions. Deep learning models are considered a black box [50] and they are one of the current challenges in the adoption of AI. AI spoilage predictions will be explained in a transparent manner to gain users' and regulators' trust in AI based decisions. The accuracy and robustness of the AI spoilage prediction models [51] will be enhanced through the combination of multiple different types of data (i.e., sensor readings, spectroscopy, image analysis and historical data).

As population is increased day by day [52] and world need more food for survival [53-56] while the global sustainability goals will witness a great reduction in food waste with the AI driven food spoilage prediction. The future of AI in this area includes: AI will suggest where surplus food is located near spoiling and suggests redistributing to food banks and charities. Mobile food storage conditions in home will be analyzed through AI powered mobile apps that will give suggestions on appropriate food storage conditions and recipes using the food to avoid wasting. The new preservation techniques that will be developed thanks to AI models include predictive fermentation control for dairy products and AI optimized cold storage strategies for perishable items [57]. Real time monitoring, block chain transparency, advanced AI models and practices for sustainable food management is what will drive the future of AI in food spoilage prediction. Whilst AI technology continues to develop, increasing its combination with IoT, block chain and edge computing will provide additional means towards food safety and reducing waste [58]. Rather than just enhancing food quality estimation and shelf life estimation, these innovations will also help create a more efficient, sustainable global food system. Finally, we will review and conclude with the core findings

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of this review and discuss the future directions of AI based food spoilage prediction from an outline for future research standpoint.

Conclusion

Integration of artificial intelligence in food spoilage prediction and shelf life estimation can transform food industry to great extent. AI can improve food safety, cut down on waste, and maximize supply chain management by using machine learning models, sensor based monitoring, and real time data analytics. This review also identified different ways in which AI has been used in food spoilage prediction including different AI models being made use of in various food spoilage prediction setups, types of data made use of, several real world applications of this technology that are currently being implemented, challenges, and finally future innovations. Specifically, AI models of machine learning and deep learning techniques predict accurately and dynamically food spoilage. The factors that are included in these models for estimation include temperature, humidity, gas emission, microbial growth and so on all of which are in excess of traditional methods of shelf life estimation.

High quality data from both IoT enabled sensors and spectroscopy analysis as well as environmental conditions and historical patterns of spoilage are a critical input to the accuracy of these AI models. Combining these various datasets boosts the AI's predictive performance. We are seeing how AI powered solutions can revolutionize food packaging, supply chain management and retail operations in order to change the game in predicting, preventing and identifying issues and inefficiencies in the food industry. Food spoilage and safety are improved by smart packaging with embedded AI sensors, food traceability based on block chain, and automated inventory management. Although AI in food spoilage prediction has the potential, there are still some challenges such as data availability problems, lack of model accuracy, high implementing cost and barriers of regulation. Research and playing together are necessary to solve these problems, involving stakeholders of the food industry, technology sector, and regulatory bodies.

Newer trends coming with the integration of AI and IoT for food spoilage prediction, use of block chain for secured food tracking and superior AI techniques like Explanable AI (XAI) and Multi modal learning will further improve the efficiency of food spoilage prediction through AI. Reducing global food waste will also rely on sustainable AI applications. Although remarkable strides have been taken toward the use of AI for predicting food spoilage, there is still room for improvement in actualizing model accuracy, scalability, and real world applications. Future studies should focus on

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Development of global food spoilage data sets with standardized data collection protocols to train AI and help improve generalization of the model. Exploring the ways of implementing explainable AI techniques for transparency and accountability in AI driven food safety decisions. Coming up with cost effective AI solutions to mitigate food spoilage problems in areas with scarce technological base. Delivering AI to tie together surplus food and food banks and charities so as to reduce food waste and address food insecurity. The revolution of producing AI food spoilage prediction is groundbreaking revolution in food safety and sustainability. Unlike most disruptions of the past, AI can address the current challenges of the food ecosystem and, at the same time, leverage future innovations. Food scientists, AI researchers, policymakers, industry leaders will need to collaborate to realize successful adoption of machine learning technologies for food spoilage estimation. For such advances in AI play a bigger part in guaranteeing worldwide food security and decreasing environmental effect.

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