International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(1):1299-1316

Review Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i01.02032

Impact of Microorganisms on Food Spoilage and Human Health: A Comprehensive Review of Advances in Identification using Image Processing and Artificial Intelligence Techniques

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Abstract

Food spoilage and human health are greatly affected by microorganisms, such as bacteria, algae, fungi, and protozoa. While traditional identification methods are reliable, they are often laborious and time-consuming. In recent years, artificial intelligence (AI) and image processing have made significant progress in identifying and classifying microorganisms quickly and accurately. In this review, we will examine image processing and artificial intelligence-based techniques for identifying and classifying microorganisms relevant to human health and food spoilage, comparing their effectiveness to traditional methods and assessing their impact on food safety. Bacteria, algae, fungi, and protozoa are the four major groups of microorganisms examined in this review. A review of applications in food safety, clinical microbiology, and environmental monitoring is presented in this paper. It examines how bacteria, yeast, and molds cause food spoilage and examines their mechanisms of action. Furthermore, the article highlights common foodborne illnesses and the health consequences of eating contaminated food. The paper also discusses advances in identifying spoilage-causing microorganisms, with a particular emphasis on artificial intelligence (AI) and image processing. With modern techniques, microbial contamination can be detected more accurately and efficiently, thus improving food safety. Finally, the review concludes by analyzing current challenges and future directions in the field, emphasizing the need for continued innovation in microbial detection methods. In the review, rapid detection of foodborne pathogens is highlighted, as well as automated spoilage monitoring. This technology has the potential to revolutionize food safety practices and clinical microbiology, so it must continue to be developed and validated.

Keywords: Algae, Bacteria, Food Spoilage, Fungi, Human Health, Impact of Microorganisms, Microorganisms, Protozoa.

Introduction

A wide range of microorganisms, including bacteria, algae, fungi, and protozoa as shown in Figure 1, play an important role in our lives, particularly in the context of food spoilage and human health. To ensure food safety, maintain product quality, and promote public health, it is vital to understand these microscopic organisms. In the food industry, food spoilage is a major problem due to its impact on economic losses and consumer health. Food spoilage is commonly attributed to microorganisms, which can alter food's appearance, odor, texture, and flavor. Because of bacteria such as Escherichia coli, Salmonella, and Listeria, severe gastrointestinal issues and potentially life-threatening complications can occur (1). Additionally, certain algae and fungi can produce mycotoxins, which cause liver damage, cancer, and neurological disorders (2). Likewise, microorganisms have a significant effect on human health, both positively and negatively (3). Probiotics are beneficial bacteria that contribute to the maintenance of a healthy gut microbiome, which is crucial for nutrient absorption, digestion, and immune system function (4). In contrast, pathogenic microorganisms, like Clostridium difficile and Helicobacter pylori, can cause severe gastrointestinal disorders, such as colitis, diarrhea, and peptic ulcers (5). The importance of identifying and classifying microorganisms for preventing food spoilage and maintaining human health cannot be overstated. By detecting these microorganisms accurately and efficiently, we can develop targeted strategies for food preservation, quality control, and public health. This review paper aims to summarize the effects of bacteria, algae, fungi, and protozoa on human health and food spoilage. As well as the associated risks and

(Received 15th August 2024; Accepted 28th January2025; Published 31st January2025)

consequences, these microorganisms will be examined in depth. To evaluate the health risks associated with these microorganisms. To evaluate whether image processing and artificial intelligence techniques are capable of identifying these microorganisms. To highlight their potential for improving food safety and public health practices, these advanced technologies will be evaluated in comparison to traditional identification methods for performance, accuracy, and limitations.

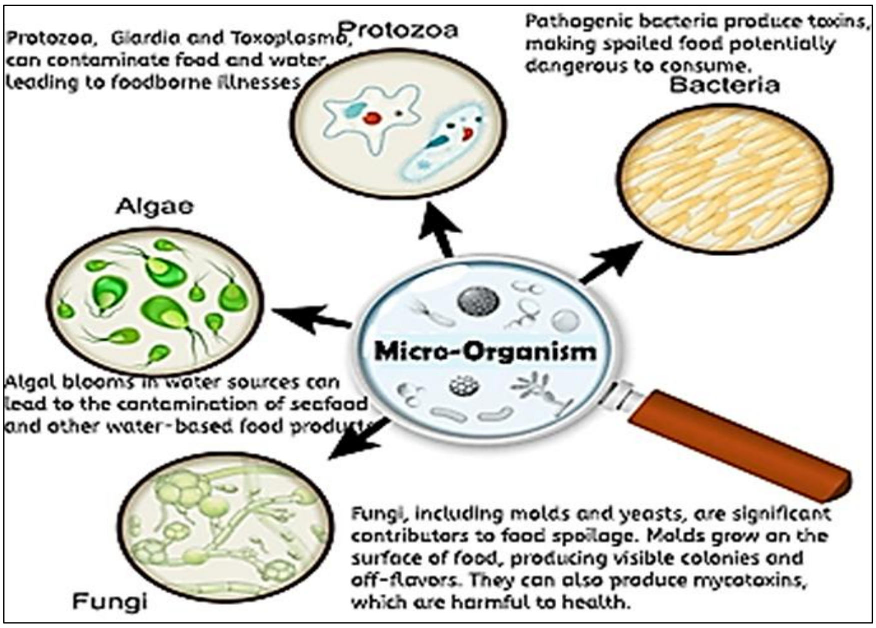

Figure 1: Types of Microorganisms (3)

Reviewing these objectives, the paper will develop a comprehensive understanding of microorganisms in food spoilage and human health, as well as emerging techniques for identifying and categorizing them. To maintain food quality and safety, microorganisms responsible for spoilage must be identified and classified. The challenge can be addressed non-invasively and rapidly with image processing. The use of advanced imaging systems can detect and distinguish bacteria, yeasts, and mold typically associated with food spoilage. Using time-lapse imaging and computer vision techniques (6) can quantify microbial growth rates on different food substrates and predict spoilage progression. Integrating environmental data with imaging results can reveal how temperature and humidity affect microbial growth patterns (7). The dynamics of food spoilage are better understood by multifaceted approaches. Food safety assessments can be significantly shortened with rapid imaging-based screening methods for detecting pathogenic microorganisms in food samples (8).

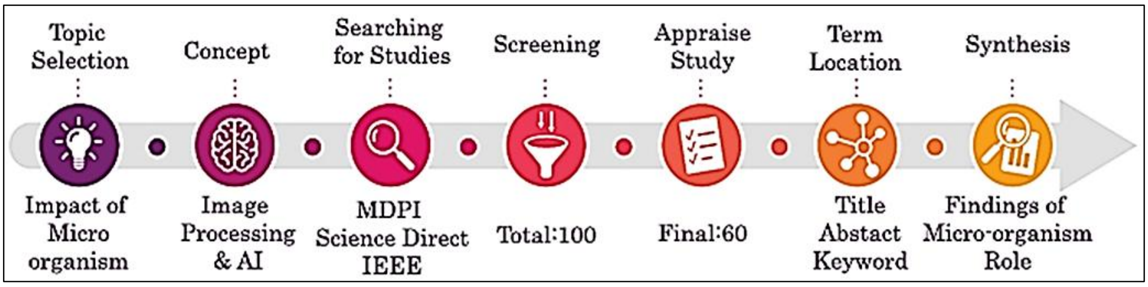

Figure 2: Search Strategy

The above-mentioned Figure 2 shows the search strategy of this study for the different microorganisms based on Food Spoilage and Health Care. The Food spoilage will be discussed in this review, including microbial growth patterns across various food types, the biochemical changes caused by microorganisms, and the sensory changes resulting from the deterioration. There are different types of spoilage microorganisms and patterns for different foods. It will include a discussion of pathogens and illnesses associated with foodborne pathogens, bacteria's ability to produce toxins, and antimicrobial resistance. Due to their efficiency, speed, and non-invasive capabilities, image processing and AI techniques increasingly relevant for microorganism identification. With these methods, large numbers of samples can be processed rapidly, identification can be automated, and microbial contamination can be detected earlier than previously thought the methods are also applicable to detecting new pathogens more quickly than conventional techniques (7, 8). By integrating these techniques with other food safety technologies, comprehensive quality control measures can be implemented in the food industry, ultimately enhancing food safety and public health.The growing global concern over food safety has focused attention on microorganisms and food spoilage. As foodborne illness prevalence increases and public health crises result, better understanding of microorganisms involved in food spoilage is urgently needed. It is critical to identify and control these microorganisms to reduce food waste, ensure food quality, and protect consumer health. In addition, the paper addresses the knowledge gap in integrating artificial intelligence and image processing into the identification and management of spoilage-causing microbes. In the current food safety scenario, it is difficult to detect and manage microorganisms responsible for spoilage effectively. Even though traditional methods of microbial identification are effective, they can be time-consuming. A revolution is underway in this field with the rise of artificial intelligence (AI) and image processing. With these modern techniques, spoilage microorganisms can be detected more accurately and faster and large datasets can be analyzed in real-time. By reducing food waste and economic losses, food safety measures are enhanced. Because of their integration into food safety protocols, these technologies provide a more effective and reliable approach to providing public health protection.

Review in Role of Microorganism in Food Spoilage

Various microorganisms can cause food spoilage and pose serious health risks. Bacteria cause most foodborne illnesses and spoilage. Various food products are frequently contaminated with Escherichia coli, Salmonella, and Listeria monocytogenes, which can cause severe gastrointestinal issues and potentially life-threatening complications (2). Although lactic acid bacteria are beneficial in food fermentation, they can affect the taste and texture of some products (9). The impact of microorganisms in food spoilage is shown in Figure 3.

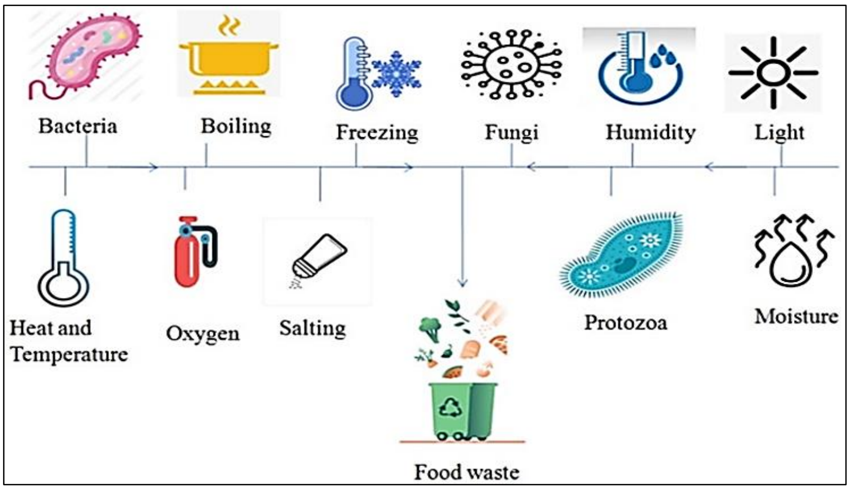

Figure 3: Microorganisms in Food Spoilage (10)

Bacteria

Food spoilage is largely caused by bacteria, causing substantial economic losses and health risks. Gram-negative psychrotrophic bacteria, especially Pseudomonas spp., primarily cause the spoilage of protein-rich foods. By producing extracellular lipases and proteases, these bacteria break down food components, causing off flavors and textures. The presence of psychrotrophic bacteria in dairy products can have a significant impact on quality. It has been found that Pseudomonas fluorescens produces heat-stable enzymes that can survive pasteurization (11). Some products can be spoilt by lactic acid bacteria (LAB), which are often beneficial in food fermentation. Vacuum-packed meat and poultry can develop slime, discoloration, and off-odors caused by LAB. Leuconostoc spp. and Lactobacillus spp. Alicyclobacillus acidoterrestris has emerged as a major spoilage organism in fruit juices, producing guaiacol that imparts a medicinal odor (12). Spoilage organisms like Shewanella putrefaciens and Photobacterium phosphoreum in seafood (13) cause the characteristic “fishy” odor of spoiled fish. The spoilage potential of bacteria extends beyond their direct effect on food. Pathogenic bacteria can grow in environments created by spoilage bacteria. As an example, certain LAB can grow in vacuum-packed meat, creating an ideal environment for Clostridium botulinum (14). Moreover, bacteria that form biofilms on surfaces or equipment may become more resistant to cleaning and sanitizing procedures, leading to spoilage (15).

Algae

A number of aquatic food sources, particularly seafood, are contaminated and degraded by algae, which are less commonly associated with traditional food spoilage than bacteria and fungi. The main concern with algae is harmful algal blooms (HABs), which influence the quality and safety of seafood. The toxins produced by certain algae can accumulate in shellfish and fish, making them unsafe for consumption. As an example, Alexandrium spp. Produce saxitoxins that cause paralytic shellfish poisoning. These toxins can pose a significant challenge for the seafood industry long after the algal bloom has dissipated (16). It is also possible for algae to affect freshwater food. A cyanobacterial bloom in a lake or reservoir can release molecules like geosmin and 2-methylisoborneol, which contribute to odors and tastes in drinking water (17). Algal blooms can deplete oxygen in water and change pH, stressing or killing farmed fish. Without prompt action, not only are economic losses caused, but also the affected stock can quickly spoil (18). In the same way, Pseudo-nitzschia produces domoic acid, a cause of amnesic shellfish poisoning. In humans, this toxin can accumulate in shellfish and fish, leading to neurological symptoms (19). Algal blooms can indirectly affect the quality of seafood. The mass mortality of fish during HABs can spoil wild-caught fish populations quickly. Even non-toxic algal blooms can produce off-flavors in fish and shellfish, called "earthy" or "musty" tastes, which greatly reduce their market value (20). As climate change progresses, HABs may become more frequent and severe, potentially affecting food spoilage and safety. This highlights the importance of continuous algal research and monitoring (21). There are some algae that are used directly in food production, but not directly in spoilage. Spirulina supplements, for example, can become contaminated with bacteria when improperly handled or stored (22).

Fungi

In the food industry, fungi, particularly molds, are major contributors to food spoilage. Consumers are often threatened by serious health risks from their mycotoxins produced by them. Among the most common fungi associated with food spoilage are Aspergillus species. For example, Aspergillus flavus produces aflatoxins, which are particularly harmful to cereals, nuts, and oilseeds. At high doses, these mycotoxins can cause acute toxicity and cause cancer (23). In the field, Fusarium species produce mycotoxins, but can continue to grow in storage. Among those issues are gastrointestinal problems and reproductive disorders caused by F. graminearum's deoxynivalenol and zearalenone production in cereals (24). When grown uncontrolled, P. roqueforti and P. camemberti can spoil dairy products, causing off-flavors and discoloration (25). Similarly, Aspergillus ochraceus and Penicillium verrucosum produce ochratoxin A, which has been linked to nephrotoxicity and can cause cancer (26). Food crops may become more contaminated by mycotoxin from climate change. Mycotoxin production may be enhanced by changing temperature and precipitation patterns, posing new challenges to food safety (27). Food preservation faces significant challenges in controlling fungal spoilage. The development of fungicide resistance and consumer demand for minimally processed foods necessitate ongoing research into novel preservation strategies (28). The nutritional and organoleptic properties of foods can also be affected by fungal spoilage. Regardless of visible growth, mold can cause off-flavors, discolorations, and texture changes (29).

A significant spoilage organism is Penicillium species, especially in fruits and vegetables. Apples and pears are susceptible to blue mold, called P. expansum. In system report patulin as a mycotoxin that suppresses immune system functions (30).

Protozoa

While protozoa are less commonly associated with food spoilage than bacteria and fungi, they can have significant impacts on food safety and quality. Direct food spoilage is not their primary concern, but contamination that can lead to food poisoning. There is a protozoan parasite called Cryptosporidium that threatens food safety. The contamination of water sources used for food processing by free-living amoebae such as Acanthamoeba and Naegleria is not directly related to food spoilage. According to the study, these amoebae are considered potential vectors for other pathogenic microorganisms in water systems (31). As discussed in the work, Food products containing water or fresh produce may be contaminated with Giardia (32). The authors stressed that effective methods should be developed to detect foodborne giardiasis and ensure proper sanitation practices (33). A contaminated water source or fresh produce can lead to cryptosporidiosis in humans. A review of Cryptosporidium's effects on food safety, who noted its resistance to water treatment methods (34). A need for improved detection methods and control strategies for food production and processing was highlighted. Food safety is also concerned about Giardia duodenalis (also known as G. lamblia or G. intestinalis). A soil or water contaminated with oocysts can harbor Toxoplasma gondii, which mostly affects meat products. A study explores the global impact of Enterobacter hepatica, including its potential for foodborne transmission, and highlights the challenges in diagnosing and controlling it (35). In the work they evaluated T. gondii in food animals and its implications for food safety, emphasizing the need for improved control measures. Several protozoan parasites affect the quality and safety of seafood in aquaculture. Fish health and seafood quality are negatively affected by protozoan parasites, which can reduce fish quality and marketability, though some of these parasites do not cause human illness. A bacterium that causes amoebiasis, Entamoeba histolytica, can contaminate food and water and cause disease.

Impact of Microorganisms in Human Health

The existence of microorganisms can be beneficial as well as dangerous. A significant impact of bacteria on human health is attributed to them, in particular. The gut microbiome, specifically bacteria, is responsible for digestion, absorption of nutrients, and maintaining the immune system. The Algae, particularly certain types of cyanobacteria, can produce toxins that can cause health problems. A harmful algal bloom can have various health effects in freshwater and marine environments. According to the work, cyanobacterial toxins cause liver damage, neurotoxicity, and skin irritation. Despite being less common than bacteria or fungi, protozoa can cause severe diseases. The malaria-causing Plasmodium species remain a significant health concern, particularly in tropical and subtropical regions by WHO, 2019 (36). While fungi in the human microbiome are less numerous than bacteria, evidence suggests they can have detrimental effects on health. Aspergillus species, such as fumigatus (37), can cause severe respiratory infections in immunocompromised individuals. Interaction between microorganisms and human health is complex. The gut microbiome has been linked to health conditions such as obesity, neurological disorders, and inflammatory bowel disease (38). Pregnant women and people suffering from immunodeficiency can be severely ill from Listeria monocytogenes infections (39). Approximately as many bacteria live in our bodies as humans, according to (40). Nevertheless, pathogenic bacteria can cause a wide range of diseases. In personalized medicine, the gut microbiome can also affect the efficacy and toxicity of medications (41). New health challenges may result from climate change, including changes in pathogenic microorganism distribution and prevalence. Temperatures may increase the frequency of harmful algal blooms and expand the range of vector-borne diseases. To develop new therapeutic approaches, it is crucial to understand the complex interactions between humans and microorganisms. The impact of microorganisms in human health is depicted in Figure 4.

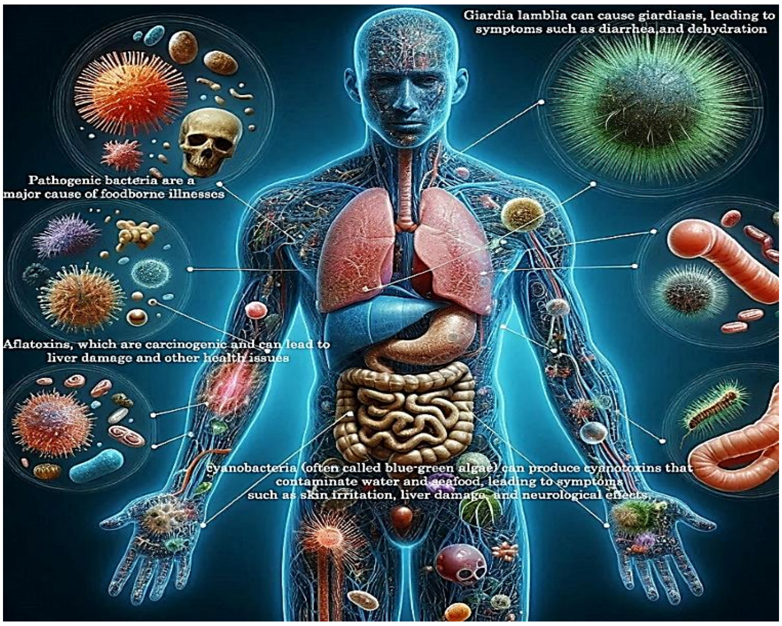

Figure 4: Impact of Microorganisms in Human Health (42)

Advances in Identification of Microorganisms

This section discusses the identification and detection techniques employed in the identification and classification of microorganisms. By using image processing, microorganisms can now be identified faster, more accurately, and more automatically than they could in the past, due to advances in image processing. With image processing, detailed morphological analyses can be conducted, automated cell counting can be performed, and colonies can be identified automatically. By analyzing complex patterns and features, artificial intelligence and machine learning further enhance microbial recognition. The study of microbial behavior and interactions is possible thanks to techniques such as 3D imaging, fluorescence analysis, and real-time monitoring. Medical diagnostics, metagenomics, and environmental monitoring are all impacted by these innovations, which transform how we study and identify microorganisms. In the following sections, we discuss methods employed, potential implications, and challenges. The following Figure 5 depicts the timeline of identification and classification of microorganisms.

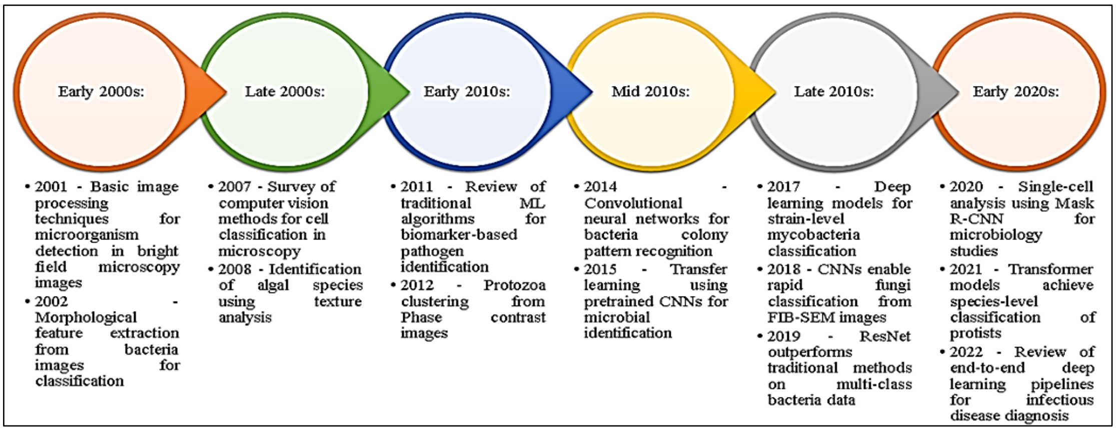

Figure 5: Timeline for Microorganisms Identification and Classification

Traditional Methods

In the food industry and clinical settings, traditional methods for microbial identification and classification have been widely used for decades. The microorganisms are typically cultured, followed by morphological, biochemical, and serological analyses. These techniques may be reliable, but they are time-consuming, laborintensive, and require specialized knowledge. Some microorganisms are difficult to culture or display similar morphological and biochemical characteristics, complicating identification. The following Table 1 describes the methods that are followed traditionally for the identification of microorganisms.

Table 1: Traditional Methods for Identifying Microorganisms

S.No.	Author (s)	Research Purpose	Challenges	Potential Implications
1.	Tournas, V. H. (43)	An overview of traditional methods for identifying spoilage microorganisms.	The process takes time and labor. Identification of some slow-growing or fastidious bacteria challenging	Detection of food spoilage microbes rapidly, leading to development of alternatives.
3.	Singh Namita. (44)	Analyze traditional microbiological methods for detecting and enumerating Escherichia coli.	A lack of differentiation between pathogenic and non-pathogenic E. coli strains	Increasing awareness of traditional coliform testing limitations
4.	Hariram *et al.,* (45)	Utilize traditional culture-based methods to identify and quantify Bacillus cereus in food.	Possibly underestimating B. cereus level due to spores.	Detection and enumeration challenges associated with B. cereus in food.
5.	Abubakar *et al.,* (46)	Analyze traditional culture-based methods for detecting Cryptosporidium and Giardia in food and water.	Traditional techniques for detecting protozoan parasites are not sensitive	Awareness of limitations of traditional methods of controlling Cryptosporidium and Giardia in food and water
6.	Gracias *et al.,* (47)	Detecting and identifying Enterococcus species in food and clinical samples using traditional and molecular methods.	On the basis of phenotypic characteristics, Enterococcus species may be misidentified	Traditional culturing and biochemical methods for detecting Enterococcus are limited
7.	Fleet G H (48)	Examine traditional methods of identifying and analyzing food spoilage yeast species.	Similar yeast species are difficult to distinguish	For rapid and reliable yeast identification, molecular and automated methods could be developed
8.	Suihko *et al.,* (49)	Identify Alicyclobacillus species in fruit juice concentrates using 16S rRNA gene sequencing.	Sequence similarities among 16S rRNA genes may misidentify Alicyclobacillus species.	Guides for selecting and combining appropriate methods for detecting these spore-forming, thermophilic bacteria

Image Processing Techniques

The field of microbial identification and classification has benefited greatly from image processing techniques. To analyze and classify microbial cells based on their morphological and structural characteristics, digital images are acquired, segmented, features extracted, and pattern recognition algorithms are used. By using image, processing techniques, microorganisms, such as bacteria, algae, fungi, and protozoa, are identified faster, more accurately, and more objectively. The success of these techniques depends on the quality of the images, the choice of appropriate image processing algorithms, and extensive training datasets. Thus, the review related to the image processing techniques takes part in the microorganisms identification is discussed in the following Table 2.

Table 2: Image Processing Techniques for Identifying Microorganisms

S.No.	Author(s)	Research Purpose	Advantages over Traditional Methods	Challenges	Potential Implications
1.	Matenda *et al.,* (50)	Using hyperspectral imaging, detect and identify spoilage bacteria in food products	Multiple samples can be analyzed simultaneously	To ensure reliable feature extraction, acquire and preprocess images accurately	A reduction in labor requirements for food microbial testing
2.	Ravanbakhsh *et al.,* (51)	Analyze the use of deep learning models to identify Salmonella and E. coli, in food samples.	Automated feature extraction from microscopic images	A large, diverse, and well-annotated training dataset is essential	Improved food safety by rapid and accurate pathogen detection
3.	Otálora *et al.,* (52)	Identify and classify microalgae species using image processing.	Analyzing microalgae samples with automation and high-throughput	Microalgae species with similar morphologies may be difficult to differentiate.	Improved monitoring and management of microalgae in water quality and biofuel production
4.	Zhang *et al.,* (53)	Analyze microscopic images to identify and classify bacteria, fungi, and protozoa using image-processing techniques.	Development of automated, high-throughput methods to identify bacteria	Adapting techniques of image processing to varying imaging modalities	Improved surveillance and control of microorganisms in various settings, including food processing, clinical diagnostics, and environmental monitoring.
5.	Wang *et al.,* (54)	Using automated image analysis techniques to enumerate microorganisms in food samples.	Improved reproducibility and objectivity in the quantification of microbial populations	Managing variation in morphology and image quality	Food quality control and safety assessments are more efficient and consistent.
6.	Zhang *et al.,*	Automated image	Microbial	Training and	Microbiology

	(55)	analysis techniques for microbe identification and classification	identification based on image processing and machine learning	benchmarking models with limited publicly available datasets	image processing methods should be further developed and integrated
7.	Satyanarayana *et al.,* (56)	Automated image analysis system for rapid identification of probiotic bacteria in food.	A faster and more accurate method of identifying probiotic strains	The challenges of reliably extracting and classifying features from images	Monitor and control probiotic-containing food products better.
8.	Omarova *et al.,* (57)	Analyze water samples for protozoan cysts and algal cysts using digital image analysis.	Methods that identify these microorganisms more quickly and objectively	Visually similar cysts of different species are difficult to distinguish	Fast and reliable protozoan and algal cyst detection for enhanced water quality monitoring
9.	Mahalakshmi Priya *et al.,* (58)	Create an integrated pipeline for the segmentation of bacterial images using microscopy.	Adaptable ROI cropping, image enhancement techniques, and specialized filtering are combined to overcome low contrast and illumination issues.	Low contrast, illumination variations, and heterogeneous bacterial shapes and textures	In microbiology, improved characterization, classification, and other analytical tasks.

Artificial Intelligence (AI) Techniques

Artificial intelligence (AI) has transformed microorganism classification by providing faster, more accurate, and automated solutions compared to traditional methods. Techniques like machine learning algorithms, such as support vector machines and decision trees, are used to classify microorganisms based on morphological or genetic features. Deep learning, particularly convolutional neural networks (CNNs), excels in image-based classification, automatically detecting patterns in microbial images. Transfer learning and ensemble learning further enhance accuracy by utilizing pre-trained models and combining multiple algorithms. These advances enable more efficient microorganism identification in fields ranging from healthcare to environmental monitoring. Machine learning and deep learning techniques have revolutionized microbial identification and classification. Because of these advanced computational methods, microbial image data can be analyzed to reveal complex patterns and relationships. The techniques of AI in the process of identifying microorganisms are discussed in Table 3 with the research ideas, challenges and potential implications.

Table 3: AI Techniques for Identifying Microorganisms

S.No.	Author(s)	Research Purpose	Advantages over Traditional Methods	Challenges	Potential Implications
1.	Shelke *et al.,* (59)	Analyze microbiology's	Analysis of complex patterns in	Datasets must be large, diverse,	A better way to detect, control,

		applications and challenges using artificial intelligence.	microbial data that are difficult to discern	and well-annotated	and monitor microorganisms in food processing, clinical diagnostics, and the environment
2.	Kang *et al.,* (60)	To identify the optimal region of interest (ROI) for bacteria identification. Apply LSTM to classify major foodborne pathogens	Detects and classifies microorganisms more accurately than traditional image analysis	In more complex scenarios, like identifying bacteria mixtures in various food matrices, validation may be required.	The technology could minimize food recalls and improve food safety risk management by providing an efficient way to identify pathogens.
3.	Fernández *et al.,* (61)	Analyze the use of machine learning algorithms to identify Candida species.	An accurate identification of Candida species compared to conventional methods	Data acquisition and sample preparation challenges	A reduction in the use of traditional identification methods in clinical microbiology
4.	Madkour *et al.,* (62)	Identify and classify microalgae species with deep learning techniques	Analyzing microalgae cells more precisely than microscopy-based methods	Identifying closely related or morphologically similar microalgae	Monitoring and management of microalgae in water quality assessment, biofuel production, and environmental remediation.
5.	Robert (63)	Identify and classify protozoan cysts and algae cysts using machine learning algorithms.	Analyses and integration into monitoring systems with high-throughput	Distinguishing visually similar cysts from different species	Monitoring and controlling water quality more effectively.
6.	Karanth *et al.,* (64)	Create deep learning models for identifying Salmonella and E. Coli from food	Analyzing food samples at high speed	Modality and food matrix adaptation challenges for deep learning	Improving food safety through microbial surveillance and control
7.	Tanui *et al.,* (65)	Identify Listeria monocytogenes and other Listeria species in food samples using machine learning.	Biochemical and molecular methods are more accurate at identifying Listeria species	The genetic diversity of Listeria species poses challenges.	Food industry surveillance and control measures improved to reduce listeriosis outbreaks.
8.	Mahalakshmi Priya *et*	Marine biology machine learning	Using machine learning, the	The identification task is time-	Marine ecosystems will

	al., (66)	approaches to identify and classify plankton automatically.	identification of multiple species of plankton is automated using the extracted features, potentially increasing research speed and consistency.	consuming, requires considerable expertise, and is resilient to variations in noise, occlusion, and illumination.	be managed better and plankton ecology and biogeochemistry will be improved.
9.	GovindaPrabhu *et al.,* (67)	Identify automated methods of identifying wild animals to support conservation efforts using AI.	Utilizes advanced AI technologies like CNNs and DQN, combined with sophisticated preprocessing techniques, to enhance efficiency and scalability of conservation monitoring.	The environment is changing, there are a lot of species, and classification accuracy is important.	Monitoring wildlife, assessing biodiversity, and managing habitats has been improved.

Machine Learning (ML) Algorithms

In food spoilage and health contexts, machine learning techniques are extensively utilized to identify and classify microorganisms.

Support Vector Machines (SVMs) is particularly useful for classifying objects based on their morphological characteristics. Using hyperspectral imaging, SVMs have been used to classify spoilage-causing bacteria in dairy products. For microbial feature analysis, SVM's hyperplane optimization ensures robust separation of classes, even in high-dimensional spaces.

Decision Trees and Random Forests microbial species can be distinguished based on environmental and morphological parameters using decision trees. By aggregating multiple tree outputs, Random Forests further improve accuracy. They have been used to differentiate microbial species in different environments, such as soil and water. For example, by using SVMs, spoilage-inducing bacteria such as Pseudomonas fluorescens can be classified using hyperspectral imaging data. By detecting contamination early, these algorithms significantly reduce waste.

Deep Learning (DL) Algorithms

The ability to extract features in a microbial sample using deep learning techniques and high accuracy has revolutionized microbial detection. **Convolutional Neural Networks (CNNs)** are excellent at detecting and classifying images (65). Microbial images can be automatically analyzed using CNNs due to their hierarchical structure. In comparison to traditional methods, CNNs have been successful in identifying Listeria monocytogenes in food samples. Adapting pre-trained models for microorganism detection in complex food matrices using transfer learning with CNNs further enhances performance.

Long Short-Term Memory Networks (LSTMs) is a highly effective algorithm for analyzing time-series data, making it suitable for the analysis of microbial growth patterns. Food storage and preservation studies have used them to track microbial population changes over time. For Example, in complex environments, CNNs combined with transfer learning have shown significant advancements in identifying pathogenic microorganisms such as Salmonella. The systems reduce false negatives and improve sensitivity, especially in the case of processed foods. Using modern AI methodologies, microbial identification has been further advanced by introducing: Transfer Learning developing accurate models is accelerated by using pre-trained models instead of large datasets. By adapting models trained on unrelated datasets, transfer learning has been used to identify microbial species in diverse environments. Using Ensemble Learning, when multiple algorithms are combined, such as Random Forests and CNNs, the model's robustness is improved and prediction variance is reduced. Water samples have been classified using this approach, improving detection accuracy under varying environmental conditions. To make the study more credible and practical, it is imperative to include detailed validation studies or real-world examples of AI-based microorganism detection. The food safety industry uses hyperspectral imaging together with artificial intelligence to detect spoilage bacteria such as Escherichia coli and Salmonella. They are capable of detecting pathogens more rapidly than traditional culture-based methods because they utilize advanced image processing techniques. The use of AI-powered diagnostic platforms in clinical microbiology has also been real-world implemented, with convolutional neural networks (CNNs) being used to identify fungal infections like Candida albicans. In these examples, AI demonstrates speed and accuracy over traditional methods, thus addressing their limitations. Through the inclusion of these case studies, the transformational potential of these technologies can be demonstrated and the gap between theory and practice can be bridged. The practicality of AI methods in detecting microorganisms is further demonstrated by their application in real-world situations. For instance, hyperspectral imaging coupled with machine learning is used in the dairy industry to detect spoilage bacteria like Pseudomonas fluorescens. By intervening early, shelf life can be extended and product safety can be ensured. The AI-based image analysis of water quality has also been used to identify harmful protozoa in drinking water supplies, such as Cryptosporidium. By integrating image segmentation and classification algorithms, these systems can detect contaminants more efficiently than traditional microscopy. It is evident from the inclusion of such use cases that AI-based methods are versatile and effective across a wide range of sectors.

Case Studies and Applications

Real-world implementations of microbial identification and classification techniques are examined in this section. Traditional, image processing, and AI-based methods are explored in diverse case studies to demonstrate their usefulness, effectiveness, and potential impact. The overall case studies and application from the discussed works is described with its role and key technology is depicted in the following Table 4.

Table 4: Case Studies and Applications

S.No.	Case Study/ Application	Role	Key Technology	Summary
1.	Microorganism enumeration in fermented dairy (10)	Food industry microbial testing streamlined	Automated microscopic image analysis	Quality control can be done more objectively by quantifying microbial populations.
2.	Detection of spoilage bacteria in dairy products (42)	Improve quality control and shelf life	Analyzing hyperspectral images	Automated system for detecting and quantifying spoilage bacteria in dairy products, enabling early intervention.
3.	Food and clinical Enterococcus identification (43)	Surveillance and control of microbes	Methods based on culture and molecular techniques	Identification of Enterococcus more accurately using complementary molecular techniques.
4.	Water and food testing for Cryptosporidium and Giardia (45)	Assessment of water and food safety	Traditional culture-based methods and molecular techniques	More sensitive and specific detection techniques are needed for these protozoan parasites due to the limitations of traditional methods.

5.	Detecting Salmonella and E. coli in meat and poultry products (50)	Food safety and foodborne illness prevention	Analysis based on deep learning	Pathogenic microorganisms can be detected and controlled quickly in food samples.
6.	Biofuel monitoring of microalgae (51)	Manage the environment and produce renewable energy	Microalgae identification using deep learning	An automated, high-throughput analysis of microalgae samples for biofuel production.
7.	Clinical identification of Candida species (60)	Improve fungal infection diagnostics	Using machine learning algorithms for mass spectrometry	Identification of Candida species from patient samples faster and more accurately.
8.	Water supply protozoan and algal cyst detection (61)	Monitoring water quality and assessing public health risks	Machine learning-based image analysis	Analyzing water samples for protozoans and algae cysts
9.	Plant Disease Identification (68)	Technology-based digitization and preservation of Tamil medicinal plant knowledge.	Models using deep learning (EEXR) and image processing techniques including RBZR Augmentation.	A combination of traditional Tamil knowledge and deep learning technology is used to identify medicinal plants leaves. An innovative deep learning model (EEXR) is used to achieve 96.71% accuracy in plant identification. This approach preserves ancestral medical knowledge and supports traditional healers.

Discussion

Several key findings have been obtained from the recent literature review on the use of image processing and artificial intelligence for microbial identification and classification: Compared to traditional culturing and microscopy-based methods, advanced image processing techniques offer significant advantages. With these advanced techniques, spoilage bacteria, foodborne pathogens, microalgae, and protozoan/algal cysts can be identified faster, more accurately, and more objectively. Microbial identification systems have been improved with artificial intelligence, particularly machine learning and deep learning algorithms. By analyzing complex patterns in microbial image data, AI-based methods can detect and classify bacteria better than traditional methods. Varieties of case studies have successfully used these advanced identification techniques, including real-time food quality monitoring, rapid foodborne pathogen detection, water quality assessment, and fungal infection diagnostics. The findings from this review demonstrate the critical role microorganisms play in food spoilage. A wide range of microorganisms, including bacteria, yeasts, and molds, have been identified as the primary cause of spoilage. In addition, contaminated food can cause foodborne illnesses, some of which can be life-threatening. It is clear from this review that advanced identification methods, especially artificial intelligence (AI) and image processing, are gaining importance. These technologies are showing great promise for improving the accuracy and speed of spoilage-causing microorganism detection. By analyzing large datasets in real-time and detecting subtle microbial growth patterns, new levels of precision can be achieved. By enabling more efficient and proactive management strategies, this advancement improves food safety and reduces the economic impact of food spoilage. Moreover, public health and food safety are profoundly impacted by these findings. Ensure the safety and quality of food supplies with the growing global population. Using AI and image processing to improve food safety protocols could revolutionize the industry, leading to safer food and fewer foodborne illnesses. Furthermore, this could reduce food waste and improve the reliability of food supplies, thereby combating food insecurity.

Challenges and Limitations

The development of image processing and artificial intelligence-based microbiome identification has made significant advances, but several challenges and limitations remain. A wide range of microorganisms, imaging conditions, and sample matrices are required for the successful implementation of these techniques. The challenge remains, however, in obtaining and curating such datasets, particularly for microorganisms and imaging scenarios that are underrepresented. The development of robust and generalizable models for a variety of imaging modalities, including brightfield microscopy, fluorescence imaging, and hyperspectral imaging, would be helpful. Obtaining reliable results across different sample types, like food, clinical specimens, and environmental samples, is another pressing issue. The consistency and reliability of images must be maintained across experiments through standardized protocols and quality control measures. It is important to note that depending on how images are acquired, preprocessed, and segmented; the results can be inconsistent, resulting in poor performance of models. Furthermore, determining whether Pseudomonas fluorescens and Pseudomonas putida are morphologically similar or not. In spite of advanced AI techniques, the subtle differences in their morphological characteristics continue to pose a challenge. Increasing public datasets, developing standardized imaging and analysis workflows, and refining AI models will be required to address these limitations. The analysis of search sources from various sources for this review is shown in Figure 6.

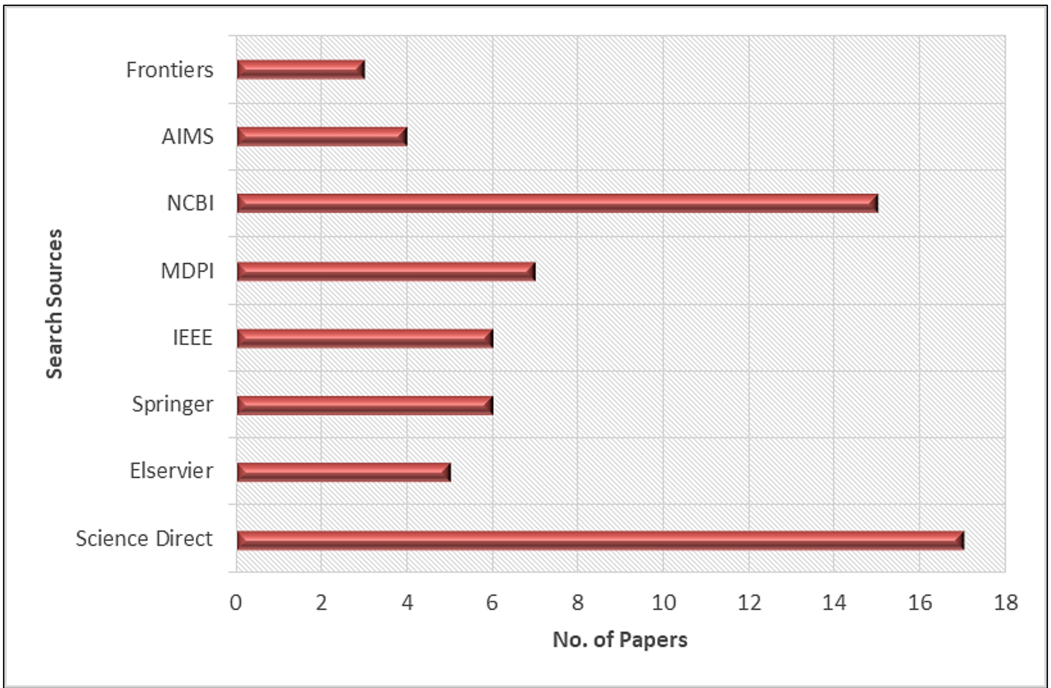

Figure 6: Analysis of Search Sources

Effectiveness of Identification Methods

In microbiology, image processing and AI techniques are powerful identification methods, but they also have limitations. As compared to traditional techniques, these methods offer an objective and faster approach to identifying microorganisms, allowing for automated analysis of large sample volumes. By uncovering patterns within microbial image data, AI enhances diagnostic precision, especially for foodborne pathogens and fungal infections. Some limitations, such as the need for comprehensive and well-annotated training datasets, counterbalance these benefits. Differentiating between closely related or morphologically similar microorganisms can also be challenging when using AI models. Moreover, if these issues are not adequately addressed, AI models may suffer from bias or overfitting, potentially affecting microbial identification accuracy and reliability.

Gaps in Current Research

In reviewing the literature on microbial identification using image processing and AI techniques, several key gaps have been identified. It is challenging to reproduce and compare findings across studies because image acquisition and processing protocols are not standardized. The issue can be addressed by developing standardized guidelines for data collection, preprocessing, and analysis. The expansion of publicly available microbial image datasets is another critical area. To advance research and improve AI models, large, diverse, and well-annotated datasets encompassing a wide range of microorganisms would be invaluable. A promising opportunity is to integrate various imaging techniques, such as fluorescence, Raman spectroscopy, with other data sources like genomics and biochemistry. In the future, this could lead to better microbial identification. Identifying closely related microorganisms is another pressing need, particularly in contexts like food spoilage and human health. In addition, these identification systems need to be validated and deployed in the real world. Developing practical, industry-ready solutions will require comprehensive testing in diverse settings, such as food processing facilities, clinical laboratories, and environmental monitoring programs.

- Detecting microbial growth with traditional methods has high labor intensity and is time consuming, making them unsuitable for high-throughput applications.
- Due to lack of standardization and insufficient datasets covering diverse imaging conditions, AI-based methods have not been widely adopted.
- It combines traditional methods with advanced microbial detection technologies in order to deal with the lack of standardized AI models.

Conclusion

Using bacterial, algae, fungus, and protozoa as examples, this review examines the current state of image processing and AI-based techniques for identifying and classifying microorganisms. Advanced methods offer significant advantages over traditional methods, including speed, objectivity, and potential accuracy, across a range of applications from food safety to clinical diagnostics. However, challenges remain, such as adapting to multiple imaging modalities, and distinguishing closely related microorganisms. Although there are hurdles, food safety and clinical microbiology could be significantly affected. Microbial image databases should be expanded, multimodal data incorporated, and extensive real-world validation undertaken in the future. Even with challenges, an integration of these technologies could revolutionize food safety practices, enhance clinical diagnostics, and improve public health outcomes. It is also important to note that there is a need for interdisciplinary collaboration between microbiologists, technologists, and public health experts to develop comprehensive strategies that can be widely adopted by the food industry in order to achieve these goals. The use of these advanced detection methods can be expanded to protect the public health, reduce the amount of food wasted, and ensure a safer supply of food for the world's population by continuing to innovate and invest in these advanced detection methods. Several emerging technologies will contribute to future advances in microbial identification, such as single cell analysis; clustered regularly interspaced short palindromic repeat (CRISPR) based diagnostic methods, and the integration of multimodal data. Using single-cell analysis, it is possible to characterize individual microbial cells in high-resolution and detect rare pathogens, identify microbial diversity, and identify antibiotic-resistant strains with unprecedented specificity. As a result, CRISPR-based diagnostics offer rapid, accurate detection of pathogens like Escherichia coli and Listeria monocytogenes in food safety and public health. Further, AI, genomics, and advanced imaging (e.g., Raman spectroscopy or hyperspectral imaging) can be integrated into the process. In addition to unraveling complex patterns, it enhances the accuracy of classification in the identification of microorganisms. A number of critical challenges, including detecting pathogens in real time, combating antibiotic resistance, and improving food safety, can be met with these innovations. Using such technologies will revolutionize public health interventions and ensure safer food systems worldwide by delivering unprecedented precision and efficiency.

Abbreviations

AI: Artificial Intelligence, LAB: Lactic Acid Bacteria, HAB: Harmful Algal Blooms.

Acknowledgement

Nil.

Author Contribution

The corresponding author confirm sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Conflict of Interest

Authors declared that there is no conflict of interest.

Ethics Approval

Not applicable.

Funding

None.

References

1. Bintsis T. Foodborne pathogens. AIMS Microbiology. 2017; 3(3):529–563.
2. Ahlberg SH, Joutsjoki V, Korhonen HJ. Potential of lactic acid bacteria in aflatoxin risk mitigation. International Journal of Food Microbiology. 2015; 207(1):87–102.
3. 123RF. Image Generator. Pathogens through a magnifying glass: Microorganisms, microbe is an organism of microscopic size [Image]. https://www.123rf.com/photo_213782329_pathogens-through-a-magnifying-glass- microorganisms-microbe-is-an-organism-of-microscopic-size.html.
4. Selhub EM, Logan AC, Bested AC. Fermented foods, microbiota, and mental health: ancient practice meets nutritional psychiatry. Journal of Physiological Anthropology. 2014; 33(1):1–11.
5. Hooi JK, Lai WY, Ng WK, Suen MM, Underwood FE, Tanyingoh D. Global prevalence of Helicobacter pylori infection: systematic review and meta-analysis. Gastroenterology. 2017; 153(2):420–429.
6. Brown DC, Turner RJ. Assessing microbial monitoring methods for challenging environmental strains and cultures. Microbiology Research. 2022; 13(2):235–257.
7. Qiu Y, Zhou Y, Chang Y, Liang X, Zhang H, Lin X, *et al.* The effects of ventilation, humidity, and temperature on bacterial growth and bacterial genera distribution. International Journal of Environmental Research and Public Health. 2022; 19(22):1-13.
8. Ndraha N, Lin HY, Wang CY, Hsiao HI, Lin HJ. Rapid detection methods for foodborne pathogens based on nucleic acid amplification: recent advances, remaining challenges, and possible opportunities. Food Chemistry Molecular Sciences. 2023; 7(1):1-17.
9. Pothakos V, Samapundo S, Devlieghere F. Total mesophilic counts underestimate in many cases the contamination levels of psychrotrophic lactic acid bacteria (LAB) in chilled-stored food products at the end of their shelf life. Food Microbiology. 2012; 32(2):437–443.
10. Sonwani E, Bansal U, Alroobaea R, Baqasah AM, Hedabou M. An artificial intelligence approach toward food spoilage detection and analysis. Frontiers in Public Health. 2022; 9(1):1-13.
11. Machado SG, Baglinière F, Marchand S, Van Coillie E, Vanetti MCD, De Block J. The biodiversity of the microbiota producing heat-resistant enzymes responsible for spoilage in processed bovine milk and dairy products. Frontiers in Microbiology. 2017; 8:1–11.
12. Pornpukdeewattana S, Jindaprasert A, Massa S. Alicyclobacillus spoilage and control - a review. Critical Reviews in Food Science and Nutrition. 2019; 60(1):108–122.
13. Kulawik P, Özogul F, Glew R, Özogul Y. Significance of antioxidants for seafood safety and human health. Journal of Agricultural and Food Chemistry. 2013; 61(3):475–491.
14. Peck M, Goodburn K, Betts R, Stringer S. Assessment of the potential for growth and neurotoxin formation by non-proteolytic Clostridium botulinum in short shelf-life commercial foods designed to be stored chilled. Trends in Food Science and Technology. 2008; 19(4):207–216.
15. Berdalet E, Fleming LE, Gowen R, Davidson K, Hess P, Backer LC. Marine harmful algal blooms, human health and wellbeing: challenges and opportunities in the 21st century. Journal of the Marine Biological Association of the United Kingdom. 2015; 96(1):61–91.
16. Lee J, Rai PK, Jeon YJ, Kim KH, Kwon EE. The role of algae and cyanobacteria in the production and release of odorants in water. Environmental Pollution. 2017; 227(1):252–262.
17. Sinden A, Sinang SC. Cyanobacteria in aquaculture systems: linking the occurrence, abundance, and toxicity with rising temperatures. International Journal of Environmental Science and Technology. 2016; 13(12):2855–2862.
18. Trainer VL, Bates SS, Lundholm N, Thessen AE, Cochlan WP, Adams NG, Trick CG. Pseudo-nitzschia physiological ecology, phylogeny, toxicity, monitoring, and impacts on ecosystem health. Harmful Algae. 2012; 14(1):271–300.
19. Watson SB, Monis P, Baker P, Giglio S. Biochemistry and genetics of taste- and odor-producing cyanobacteria. Harmful Algae. 2016; 54(1):112–127.
20. Wells ML, Trainer VL, Smayda TJ, Karlson BS, Trick CG, Kudela RM, *et al.* Harmful algal blooms and

climate change: learning from the past and present to forecast the future. Harmful Algae. 2015; 49(15):68–93.

21. Wells ML, Potin P, Craigie JS, Raven JA, Merchant SS, Helliwell KE. Algae as nutritional and functional food sources: revisiting our understanding. Journal of Applied Phycology. 2016; 29(2):949–982.
22. Alshannaq A, Yu JH. Occurrence, toxicity, and analysis of major mycotoxins in food. International Journal of Environmental Research and Public Health. 2017; 14(6):1-20.
23. Ferrigo D, Raiola A, Causin R. Fusarium toxins in cereals: occurrence, legislation, factors promoting the appearance, and their management. Molecules. 2016; 21(5):1-35.
24. Garnier L, Valence F, Pawtowski A, Auhustsinava-Galerne L, Frotté N, Baroncelli R. Diversity of spoilage fungi associated with various French dairy products. International Journal of Food Microbiology. 2017; 241(1):191–197.
25. Malir F, Ostry V, Pfohl-Leszkowicz A, Malir J, Toman J. Ochratoxin A: 50 years of research. Toxins. 2016; 8(7):1-49. https://doi.org/10.3390/toxins8070191.
26. Medina A, Akbar A, Baazeem A, Rodriguez A, Magan N. Climate change, food security, and mycotoxins: do we know enough? Fungal Biology Reviews. 2017; 31(3):143–154.
27. Van Long NN, Joly C, Dantigny P. Active packaging with antifungal activities. International Journal of Food Microbiology. 2016; 220(1):73–90.
28. Pitt JI, Hocking AD. Fungi and food spoilage. In: Springer eBooks. 2009; 1–27. https://link.springer.com/book/10.1007/978-0-387-92207-2.
29. Tannous J, Atoui A, Khoury AE, Francis Z, Oswald IP, Puel O, Lteif R. A study on the physicochemical parameters for Penicillium expansum growth and patulin production: effect of temperature, pH, and water activity. Food Science and Nutrition. 2016; 4(4):611–622.
30. Bacanli M, Dilsiz SA, Başaran N, Başaran AA. Chapter Five - Effects of phytochemicals against diabetes. In: Toldrá F, editor. Advances in Food and Nutrition Research. Academic Press; 2019; 89:209–238. ISSN 1043-4526.
31. El Sheikha AF. Molecular detection of mycotoxigenic fungi in foods: the case for using PCR-DGGE. Food Biotechnology. 2019; 33(1):54–108.
32. Hussain M, Stitt V, Szabo E, Nelan B. Toxoplasma gondii in the food supply. Pathogens. 2017; 6(2):1-7.
33. Ryan U, Hijjawi N, Xiao L. Foodborne cryptosporidiosis. International Journal for Parasitology. 2018; 48(1):1–12.
34. Shirley DA, Farr L, Watanabe K, Moonah S. A review of the global burden, new diagnostics, and current therapeutics for amebiasis. Open Forum Infectious Diseases. 2018; 5(7):1–9.
35. Huisman J, Codd GA, Paerl HW, Ibelings BW, Verspagen JMH, Visser PM. Cyanobacterial blooms. Nature Reviews Microbiology. 2018; 16(8):471–483.
36. World Health Organization. Malaria. World Health Organization. 2019; Fact Sheet. Available from: https://www.who.int/news-room/fact-sheets/detail/malaria.
37. Latgé JP, Chamilos G. Aspergillus fumigatus and aspergillosis in 2019. Clinical Microbiology Reviews. 2019; 33(1):1–46.
38. Lynch SV, Pedersen O. The human intestinal microbiome in health and disease. New England Journal of Medicine. 2016; 375(24):2369–2379.
39. Radoshevich L, Cossart P. Listeria monocytogenes: towards a complete picture of its physiology and pathogenesis. Nature Reviews Microbiology. 2017; 16(1):32–46.
40. Sender R, Fuchs S, Milo R. Revised estimates for the number of human and bacterial cells in the body. PLoS Biology. 2016; 14(8):1–20.
41. Zimmermann M, Zimmermann-Kogadeeva M, Wegmann R, Goodman AL. Mapping human microbiome drug metabolism by gut bacteria and their genes. Nature. 2019; 570(7762):462–467.
42. Freepik. AI Image Generator. Picture of a human body with the word "bacteria" on it [Image]. https://www.freepik.com/premium-ai-image/picture-human-body-with-word-bacteria-it_322153781.htm
43. Tournas VH. Spoilage of vegetable crops by bacteria and fungi and related health hazards. Critical Reviews in Microbiology. 2005; 31(1):33–44.
44. Singh N. Evaluation of E. coli bacteria in different food samples. International Journal on Life Science and Bioengineering. 2016; 3(1):13–19.
45. Hariram U, Labbé R. Spore prevalence and toxigenicity of Bacillus cereus isolates from U.S. retail spices. Journal of Food Protection. 2015; 78(3):590–596.
46. Abubakar I, Irvine L, Aldus C, Wyatt G, Fordham R, Schelenz S, *et al.* A systematic review of the clinical, public health, and cost-effectiveness of rapid diagnostic tests for the detection and identification of bacterial intestinal pathogens in feces and food. Health Technology Assessment. 2007; 11(36):1–65.
47. Gracias KS, McKillip JL. A review of conventional detection and enumeration methods for pathogenic bacteria in food. Canadian Journal of Microbiology. 2004; 50(11):883–890.
48. Fleet GH. Yeast spoilage of foods and beverages. In: Yeasts in Food and Beverages. Springer eBooks [Book Chapter]; 2009; 53–63. https://doi.org/10.1016/b978-0-444-52149-1.00005-7.
49. Suihko ML, Stackebrandt E. Identification of aerobic mesophilic bacilli isolated from board and paper products containing recycled fibers. Journal of Applied Microbiology. 2003; 94(1):25–34.
50. Matenda RT, Rip D, Marais J, Williams PJ. Exploring the potential of hyperspectral imaging for microbial assessment of meat: a review. Spectrochimica Acta Part A Molecular and Biomolecular Spectroscopy. 2024; 315(5):1-12.
51. Ravanbakhsh M, Ngom A, Jeong C. Deep learning models for microorganism identification in food safety. IEEE International Conference on Bioinformatics and Biomedicine (BIBM). 2021; 1(1):2705–2711.
52. Otálora P, Guzmán J, Acién F, Berenguel M, Reul A. Microalgae classification based on machine learning techniques. Algal Research. 2021; 55(4):1-9.

53. Zhang Y, Jiang H, Ye T, Juhas M. Deep learning for imaging and detection of microorganisms. Trends in Microbiology. 2021; 29(7):569–572.
54. Wang L, Wu Z. A simple high-throughput technology for microorganism detection and quantitative analysis. Foods. 2024; 13(18):1-12.
55. Zhang J, Li C, Rahaman MM, Yao Y, Ma P, Zhang J, Zhao X, Jiang T, Grzegorzek M. A comprehensive review of image analysis methods for microorganism counting: from classical image processing to deep learning approaches. Artificial Intelligence Review. 2021; 55(4):2875–2944.
56. Satyanarayana KV, Rao NT, Bhattacharyya D, Hu YC. Identifying the presence of bacteria on digital images by using asymmetric distribution with k-means clustering algorithm. Multidimensional Systems and Signal Processing. 2021; 33(2):301–326.
57. Omarova A, Tussupova K, Berndtsson R, Kalishev M, Sharapatova K. Protozoan parasites in drinking water: a system approach for improved water, sanitation, and hygiene in developing countries. International Journal of Environmental Research and Public Health. 2018; 15(3):1-18.
58. Mahalakshmi Priya R, Sumathi M. An integrated approach to bacteria structure detection using Frangi-thresholding segmentation and its impact on analysis. Proceedings of RAEEUCCI. 2024; 2(1):1-6.
59. Shelke YP, Badge AK, Bankar NJ. Applications of artificial intelligence in microbial diagnosis. Cureus. 2023; 15(11):1-12.
60. Kang R, Park B, Ouyang Q, Ren N. Rapid identification of foodborne bacteria with hyperspectral microscopic imaging and artificial intelligence classification algorithms. Food Control. 2021; 130(1):1-10.
61. Fernández-Manteca MG, Ocampo-Sosa AA, De Alegría-Puig CR, Roiz MP, Rodríguez-Grande J, Madrazo F, *et al.* Automatic classification of Candida species using Raman spectroscopy and machine learning. Spectrochimica Acta Part A Molecular and Biomolecular Spectroscopy. 2023; 290(2023):1-12.
62. Madkour DM, Shapiai MI, Mohamad SE, Aly HH, Ismail ZH, Ibrahim MZ. A systematic review of deep learning microalgae classification and detection. IEEE Access. 2023; 11(1):57529–57555.
63. Robert G. Yaege. [Book Chapter]. Available from: https://www.ncbi.nlm.nih.gov/books/NBK8325/#_ncbi_dlg_citbx_NBK8325.
64. Karanth S, Patel J, Shirmohammadi A, Pradhan AK. Machine learning to predict foodborne salmonellosis outbreaks based on genome characteristics and meteorological trends. Current Research in Food Science. 2023; 6(1):1-10.
65. Tanui CK, Benefo EO, Karanth S, Pradhan AK. Machine learning model for food source attribution of Listeria monocytogenes. Pathogens. 2022; 11(6):1-12.
66. Mahalakshmi Priya R, Barani R, Sumathi M. Machine learning for plankton species identification and classification: a new era in marine ecology. Proceedings of ICIRCA. 2023; 1(2):101-108.
67. Govindaprabhu GB, Sumathi M. Safeguarding humans from attacks using AI-enabled (DQN) wild animal identification system. International Research Journal of Multidisciplinary Scope (IRJMS). 2024; 3(3):285–302.
68. Govindaprabhu GB, Sumathi M. Ethnomedicine of indigenous communities: Tamil traditional medicinal plants leaf detection using deep learning models. Procedia Computer Science. 2024; 235(1):1135–1144.