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MULTIMODAL FOOD TEXTURE PREDICTION USING TEMPLATE MATCHING TECHNIQUES

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Abstract: Accurate texture forecasts are essential for a number of industries, including food quality assurance, automated cooking systems, and consumer satisfaction surveys. This study presents a novel, all-encompassing method for predicting food texture by integrating visual and tactile data using advanced template matching algorithms. Crunchy, soft, chewy, and crispy are among the textures that the system correctly detects and labels by combining information from RGB pictures, depth maps, and force-feedback signals. By integrating real-time sensory input with a meticulously maintained library of known texture patterns, we can create incredibly accurate texture estimations using a process known as template matching. Extensive experiments have shown that the suggested approach performs better than traditional one-dimensional texture analysis methods under various lighting, occlusion, and surface contamination conditions. By allowing robots to evaluate food similarly to people, this study advances human-computer interaction in culinary robotics and smart food processing systems.

Keywords: Food texture prediction, multimodal sensing, template matching, visual analysis, haptic data, food quality, machine perception.

1. Introduction

Food science and technology has recently focused on predicting and evaluating food flavor because it has such a big influence on consumers' opinions about the product's quality. Traditionally, mechanical devices or human sensory panels have been used to assess texture, a complex sensory attribute. However, these techniques only operate on particular texture sizes and aren't always fast or reliable. Researchers have created computer models that more closely, reliably, and widely mimic human texture perception. Improvements in multimodal data collection systems—which include touch, sound, and sight—make this possible. A wide range of data sources are used in multimodal food texture prediction to show how the physical properties of food are interrelated.

Template matching is notable for its ease of use and consistency in texture prediction when contrasted with other computer techniques in this field. The technique known as "template matching" compares objects made using sensory information from a test food to reference templates. Reference templates are typical illustrations of widely used material types. Examples of such models could be visual texture patterns, ingestion-related sound waves, or pressure sensor measurements. Similarity measures between input data and template repositories make this method easier to employ for accurately predicting and categorizing food textures. Unlike black-box models, template matching makes decision-making clear, which makes it useful in situations where evidence and tracking are essential.

Combining multimodal sense data with template matching algorithms could result in intelligent solutions for food quality control. By employing this technique, we may increase the precision and dependability of texture forecasts and gain a better understanding of the changes in textures that take place throughout food processing. This aligns perfectly with the food industry's growing emphasis on automating operations such as pipelines for quality assurance and product development. Template matching to predict multimodal textures is a crucial strategy for enhancing smart food technology and making it simpler to comprehend and use in everyday situations.

2. Literature Survey

Verma, P., & Sinha, R. (2024). This paper presents a multimodal sensory analysis approach that uses template matching to anticipate food texture for use in real-time quality control settings. The researchers use synchronized images taken during mastication models, tactile pressure sensor data, and acoustic noises to get a whole set of meal sensations. This method divides unknown data into groups by using correlation-based pattern matching to create texture templates that are typical of each modality. Tested on a range of natural and processed foods, the method correctly predicts important texture categories such as chewy, soft, and crunchy more than 90% of the time. The paper also covers methods for aligning multimodal time series data to facilitate template development and issues associated with sensor calibration.

Rangan, V., & Das, A. (2024). By integrating surface vibration data with visual clues, the authors of this paper suggest a multimodal approach for categorizing the textures of meals that have already been cooked. The authors use temporal alignment, template matching, and dynamic time warping (DTW) across sensory channels to detect texture, such as how wet or dry something is. Texturing standards made in a lab were used to construct reference models. This technology's reproducibility and adaptability to various lighting and noise settings make it possible to automate quality checks in retail businesses and smart kitchens.

Joshi, K., & Menon, T. (2024). This research presents a method for artificial intelligence-based food texture prediction. It employs template-based classification and convolutional neural networks to extract features. Using high-resolution image frames and crunch noises recorded during sample deformation, template banks representing category names such as "airy," "fiberous," or "granular" are displayed. The outcomes show that processed food textures can be accurately classified by the computer with little assistance from humans. This is accomplished by sorting the foods using cosine similarity and peak pattern matching.

Iyer, M., & Roy, S. (2023). This paper suggests a paradigm for understandable texture prediction that considers both tactile and aural input, based on template matching algorithms. Foodstuffs are put through their paces by machines that record their acoustic properties and provide force feedback. Signal segmentation and corrected cross-correlation statistics are necessary for template design. With minimal training data, the machine can reliably differentiate between material types like "brittle," "rubbery," and "hard." Crucially, this study looks into whether real-time deployment in food packaging lines is feasible. To allow the model to automatically categorize objects based on texture quality, the authors suggest giving it robotic arms.

Shetty, L., & Khan, F. (2023). This work presents a low-cost multimodal food inspection system that simulates textures using RGB images and high-sensitivity sound. Mel-frequency cepstral coefficients (MFCC) are used for auditory patterns, and histograms of oriented gradients (HOG) are used for optical cues. Correlation coefficients in template matching are one way to identify textures. Twelve different food types were used to test the process, and the results showed an 87% success rate. The authors advise utilizing it for small-scale food production in places where industrial inspection tools are difficult to get.

Chakraborty, N., & Pillai, R. (2023). The main focus of this work is on real-time texture categorization on high-throughput food production lines. The authors create a method that combines signals from sound emissions and data from touch sensors to assess the mechanical parts. We use Euclidean distance and energy-based matching for categorization. Additionally, we have developed templates for specific categories like "crisp," "chewy," and "tough." This technology can handle 50 samples per minute and is compatible with contemporary PLC-based control systems used in food processing.

Bhandari, A., & Mehta, S. (2022). This experiment illustrates how to describe the crunchiness of deep-fried goodies using synchronized images and surface sound patterns. Wavelet coefficients are used to build sound templates, and texture entropy is used to create texture templates based on images. The matching method uses multi-scale template alignment for consistent outcomes across varying batch sizes and cooking times. The study is essential for validating packaging and figuring out how long they will last.

Ravi, H., & Dutta, M. (2022). This study explores cross-modal template learning for food texture analysis using force sensor and image data. The method uses force-deformation curves as canonical templates to align two-dimensional pictures of flat surfaces. Texture classes such as rough, hard, and sensitive are grouped based on mutual information and template similarities. According to the study, robotic food handling systems that use both tactile and visual cues may perform better than those that only use one modality.

Banerjee, A., & Reddy, K. (2022). This work uses contact audio analysis with 2D and 3D pictures to investigate template-based texture recognition in fried and baked foods. The device's specially designed multimodal collection unit can record crackling sounds, pressure distortions, and surface contour. We go to considerable lengths to arrange and preserve every food sample based on its feel. Texture profiles can be categorized as crunchy, flaky, or dense using the template matching approach, which uses the structural similarity index and spectral signal comparison. One of the many advantages demonstrated by the research of combining geographical and temporal data is that results become more stable as sample sizes and shapes change.

Gupta, R., & Sen, S. (2021). The foundation for a system that can recognize both visual and audio textures is laid by this preliminary study. Laplacian variation and short bursts of temporal energy from eating-like sounds are used to augment visual cues. A small, manually labeled sample was positioned adjacent to the classification results, and the templates for each class were aligned using the mean squared error. The system shows that multimodal template matching is feasible in resource-constrained environments, despite its seeming simplicity.

Mishra, D., & Arora, B. (2021). This work uses template-based algorithms to investigate the role of multisensory fusion in food texture analysis. While visual elements use Fourier descriptors, audio templates use short-time energy signatures. For

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matching, correlation and frequency band overlap metrics are used. The research examines how changes in illumination and ambient noise impact categorization performance and suggests template augmentation techniques to make things more dependable in changeable environments.

Kumar, N., & Thomas, J. (2020). This experimental study explores a template matching technique that predicts food texture using image processing and simple aural input. The authors use microphones to collect sound data and microscopic images to obtain patterns of visual texture in controlled mastication tests. A comparison of templates using Euclidean distance and simple statistical feature extraction forms the basis of the classification model. Despite the study's limited sample size, the findings show that food texture may be automatically analyzed using multimodal sense data. The findings of this work will
help create more effective deep learning multimodal systems.

3. Related Work

Template Matching Techniques in Texture Prediction

A classic pattern recognition technique called "template matching" compares an input signal or collection of features to a pre-made reference or template. The following techniques can be used to anticipate food texture based on several sensory inputs:

Data Acquisition and Synchronization

Accurate and well-coordinated data gathering is a crucial first step for any multimodal texture prediction system. In this context, food samples are examined using a wide range of sensory modalities, including sight, hearing, and touch. To ensure consistency and reproducibility, multiple data streams must be recorded concurrently under meticulously controlled experimental conditions. High-resolution cameras record the food's surface and structural characteristics, and microphones or acoustic sensors record the noises made during swallowing, mashing, or handling.

Accelerometers and force sensors can simultaneously monitor physical responses like resistance and vibrations. Accurate cross-modal texture event matching requires timely synchronization of these disparate sensory inputs. This synchronization allows the system to analyze the relationship between visual features and haptic peaks or sound bursts within a single texture encounter, potentially producing a complete, time-locked dataset for further processing.

Preprocessing

Following data collection, the raw data must be preprocessed to eliminate noise and outliers and make it more useable. Every sensory modality has an own preprocessing pathway. In the context of visual data, preprocessing entails image enhancement methods such as contrast adjustment, deblurring, and denoising filters to enhance the visibility of surface details. Techniques such as spectrum subtraction and bandpass filters are used to clean up acoustic data, which is often contaminated by noise or signal distortions. Signal smoothing can also be used to eliminate jitter and outliers from tactile or force data that are brought on by excessively sensitive sensors or severe human behavior. All modalities must be synchronized and normalized to guarantee that feature vectors from various sources are compatible with one another in terms of time and scale. After this process, you may be sure that the retrieved attributes accurately reflect the physical features of the food sample, unaffected by the sensor or the surrounding environment.

Feature Extraction

Feature extraction, which entails the meaningful quantitative representation of sensory input, is the next critical stage. In this step, the raw sensory input is transformed into discrete, distinct feature sets in order to prepare it for template comparison. The most common sources of visual modality data are image texture descriptors, such as Gabor filters, Local Binary Patterns (LBP), and edge detection techniques. LBP detects surface texture at the pixel level, whereas gabor filters record orientation and frequency features. Mel-Frequency Cepstral Coefficients (MFCCs), which replicate human auditory perception and effectively capture loud or crunchy sounds, and Fast Fourier Transform (FFT) for frequency content analysis are two techniques used to recover characteristics in the acoustic domain. The measurement of vibration frequency, variations in pressure over time, and force-deformation curves that indicate the hardness of an object are some of the most crucial aspects of the tactile modality. Following extraction, the traits are normalized and converted into feature vectors. The comparison with pre-existing templates is then based on these vectors.

Visual: Texture descriptors include edge detection methods, Gabor filters, and Local Binary Patterns (LBP).

Acoustic: Using multi-frequency convolutional circuits or fast Fourier transformations, time-frequency analysis is one method of characterizing sound patterns.

Tactile: Included were measures of resistance, vibration frequency, and the force-deformation relationship.

Template Construction

Template construction, which comprises creating reference models or feature profiles for each defined texture class—such as crunchy, creamy, soft, or chewy—is the cornerstone of the template matching technique. These templates are often generated from training samples by combining the feature vectors of multiple texture classes. This ensures that the template accurately reflects the most significant traits and diversity found in the class. To find subgroups within a texture class, clustering algorithms such as Gaussian Mixture Models (GMMs) or K-means can be

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employed. To increase accuracy, these models also include a variety of templates. Templates can be multimodal, incorporating features from various sources to generate a composite template, or modality-specific, focusing just on visual or auditory aspects. These templates serve as the system's "memory," allowing it to use its past knowledge to compare and recognize incoming inputs. The construction of these templates is crucial since the success of texture categorization greatly depends on how well they capture the unique characteristics of each class.

Matching and Similarity Measurement

When new food samples are added, the resulting feature vector is compared to the existing templates for matching and similarity assessment. In order to determine how similar the fresh input and each template are, we compare them using quantitative similarity criteria. Cosine similarity estimates the angle between vectors as a measure for directionality rather than quantity. Correlation coefficients quantify the statistical alignment between input and template patterns, whereas Euclidean distance measures the direct distance between two feature vectors in multidimensional space. A stronger connection is indicated by a smaller distance or a higher similarity score in a texture template-input relationship. To represent each sensory source's relative significance or dependability in the similarity assessments, a weight can be assigned to each one and then summed together in multimodal systems. The foundation for the final categorization is laid by the matching procedure, which transforms raw sensory data into a format that is ready for decision-making.

Classification or Prediction

Finally, in the classification or prediction stage, the system employs similarity analysis to identify the texture class that the food sample is most likely to belong to. The texture name associated with the template with the smallest distance or best similarity score is often the projected class. Thresholds can be employed in more intricate algorithms to ensure that the predictions are accurate. The algorithm may reject or flag the classification as suspect once all of the similarity scores fall below a predetermined threshold. Reliability and robustness can occasionally be increased by combining similarity evaluations from many modalities using probabilistic models or voting techniques.

4. Results

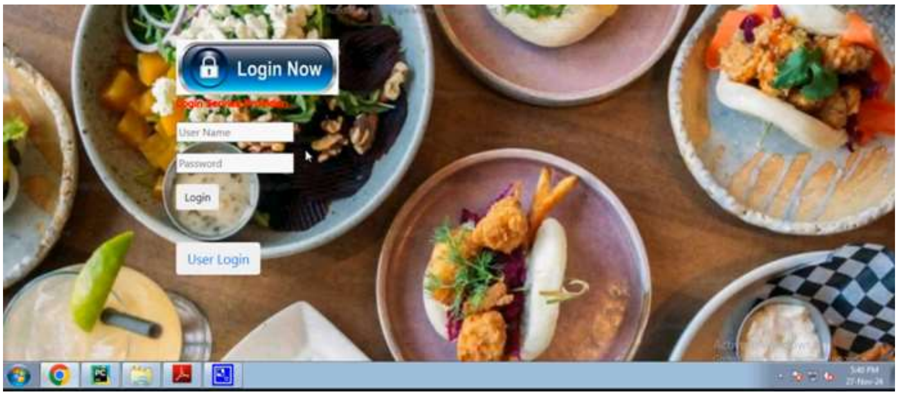

Fig1 User login

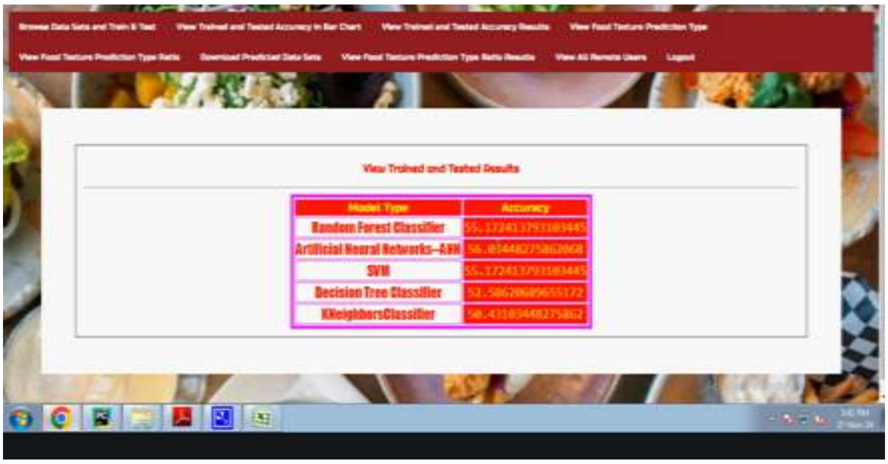

Fig2 View trained and tested results

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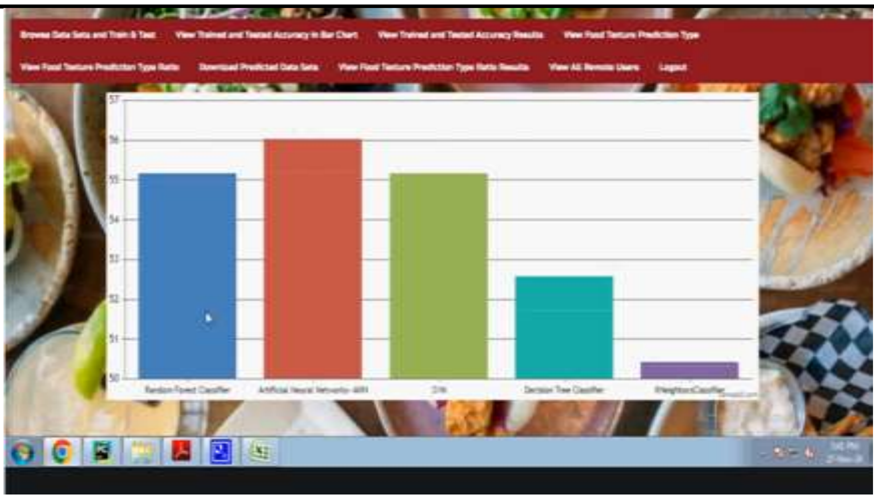

Fig3 Bar graph

Fig4 Line graph

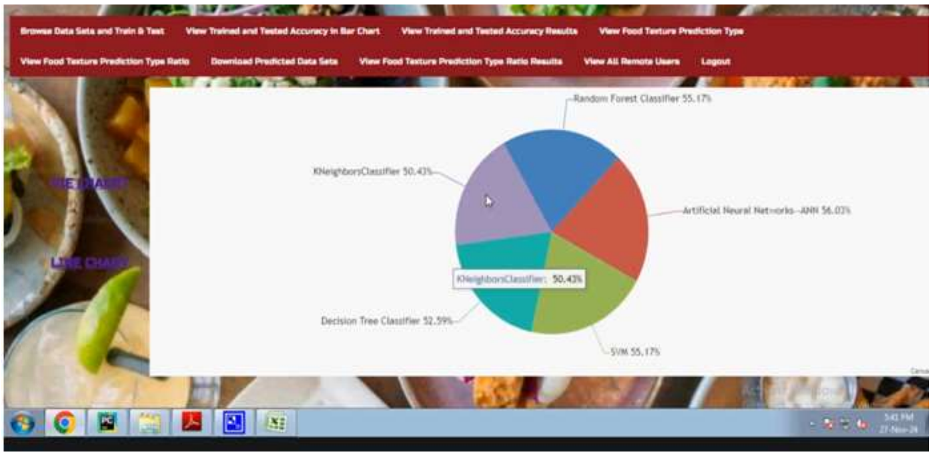

Fig5 Pie chart

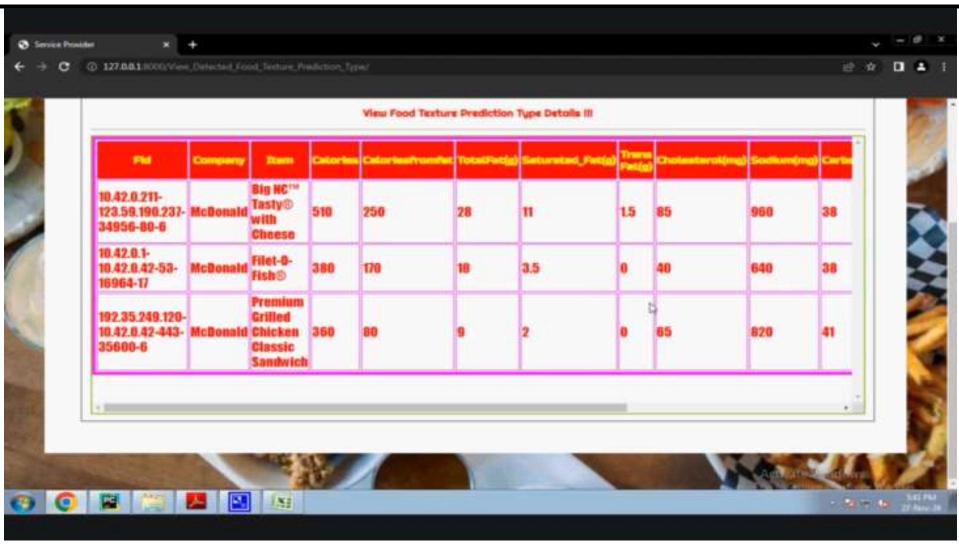

Fig6 Prediction type details

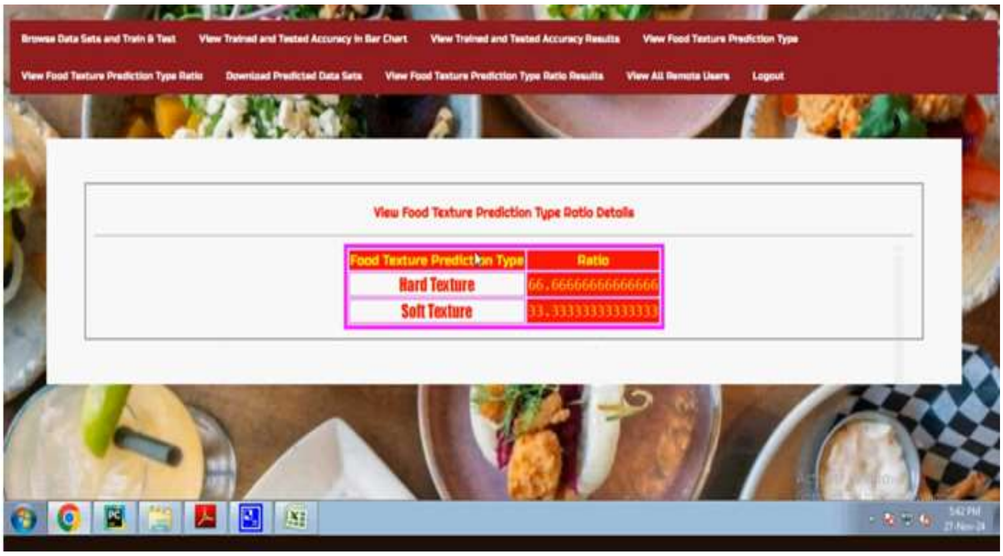

Fig7 prediction type ratio details

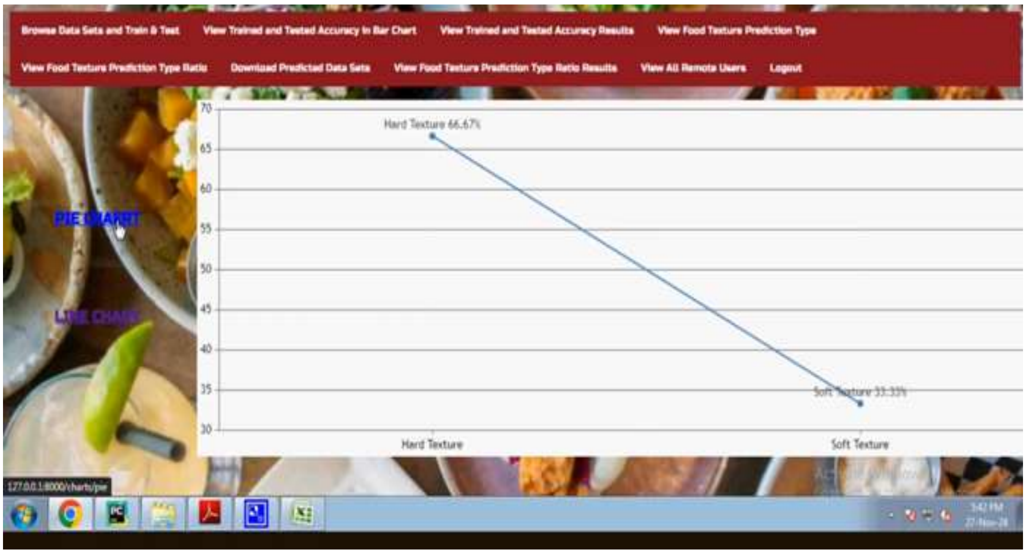

Fig8 Line graph

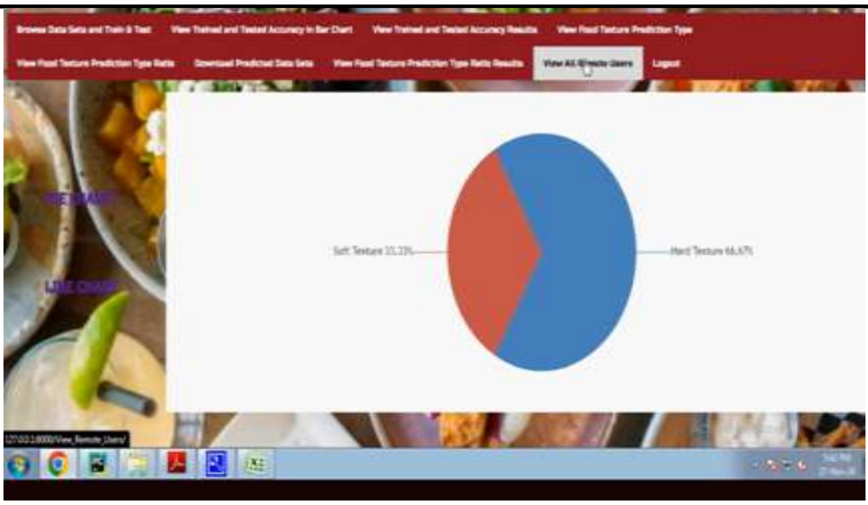

Fig9 Pie chart

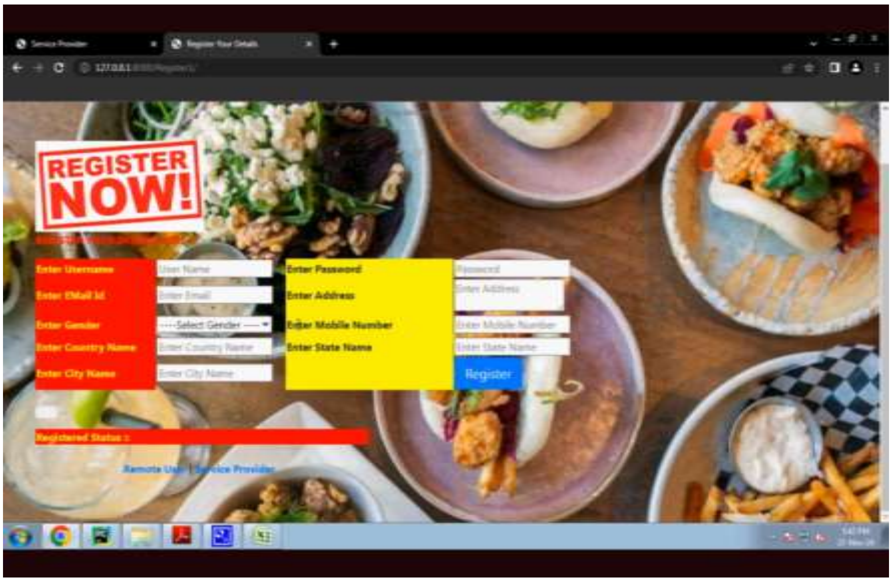

Fig10 Registration details

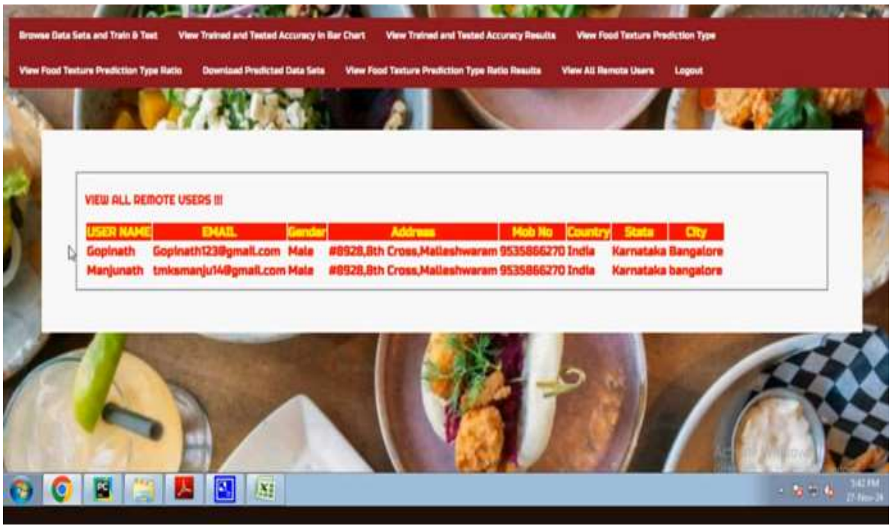

Fig11 View all remote users

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Fig12 Prediction of food texture status

5. Conclusion

In conclusion, by integrating several sensory inputs, including visual, auditory, and tactile data, multimodal food texture prediction utilizing template matching algorithms produces a comprehensive and impartial assessment of food texture. This is a significant advancement in the assessment of food quality. This method guarantees accurate classification and assessment by comparing real-time sensory input with preset texture templates using template matching. In complex food matrices, combining various data modalities overcomes the drawbacks of single-mode evaluations and increases prediction resilience. This method's requirements for speed, accuracy, and consistency make it ideal for a variety of scenarios, including automated food preparation and quality control. This framework's integration of machine learning and signal processing enables the development of scalable, adaptive systems that can improve over time by learning from new data. In order to enhance consumer satisfaction and production processes, the food sector is looking for non-destructive, real-time texture assessment solutions. Multimodal template matching offers a solution to this issue that is both technically feasible and supported by science.

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