Enhancing Precision in Spice Bag Dispensing for Noodle Cup Production through Automated Fuzzy Inference System Integration

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ABSTRACT
This paper delves into the integration of an advanced spice bag dispensing system within the Noodle cup production line, focusing specifically on fried noodles. At the heart of this system lies a meticulously designed fuzzy inference system, engineered to enhance precision and adaptability in the identification and placement of spice bags. Leveraging real-time inputs from cameras, production line speed, and spice bag characteristics, the fuzzy system dynamically applies a set of rules, ensuring precise dispensing in the face of uncertainties and variations inherent in the production environment. Drawing comparisons with a scenario involving the classification of 350 collected photos, this study highlights the adaptability and precision of the fuzzy inference system. The results showcase outstanding performance, including an accuracy of 91.43%, precision of 88.24%, recall of 93.75%, and an F1 score of 90.91%. This developed system significantly contributes to elevating the quality of instant noodle production by ensuring the presence of spice packets in all final products, thereby guaranteeing actual quality despite the high-speed nature of the production line. Operating at a rate of 60,000 cartons in an 8-hour workday, each containing 24 cups of instant noodles, this system ensures heightened efficiency and productivity, maintaining a consistently high flavor profile in the production of instant noodle cups.

Keywords
Dispensing System, Fuzzy Inference System, Instant Noodle Quality Enhancement, Efficiency and Productivity.

1. INTRODUCTION
The symbiotic relationship between Artificial Intelligence (AI) and Machine Learning (ML) has redefined processes across diverse industries, and the food production sector stands as a notable beneficiary of these advancements. This essay explores the overarching impact of AI and ML in food production and delves into their specific applications within the realm of noodles manufacturing. Artificial intelligence and machine learning are transformative forces in the food production landscape. These technologies optimize various facets of the supply chain, from predictive analytics in agriculture to inventory management and demand forecasting[1]. By leveraging AI, food producers can minimize waste, enhance sustainability, and ensure a more streamlined and efficient production process. Noodles manufacturing, as a subset of the broader food production sector, has embraced AI and ML technologies to enhance every stage of the production cycle.

Artificial intelligence (AI) has been widely recognized as a key enabler of automation, efficiency, and quality assurance in the food industry. Comprehensive studies report that AI techniques including machine learning, computer vision, and intelligent decision-support systems are increasingly adopted to improve production consistency, reduce human error, and enhance operational efficiency across food manufacturing processes [1]. In noodle production systems, research has focused on optimizing workflows and mitigating ergonomic and operational risks in high-throughput environments, such as cassava and instant noodle manufacturing lines [2]. Within instant noodle factories, AI-based computer vision systems have been applied to quality control tasks, including automatic inspection of seasoning packets to ensure their correct presence and placement [3]. Recent advancements further employ deep learning–based object detection models, such as improved YOLO architectures, to accurately count and verify packaged products at high speeds, thereby enhancing reliability and reducing miscounts on production lines [4].

To manage uncertainty and variability inherent in industrial environments, fuzzy logic–based decision-making frameworks have gained significant attention due to their ability to handle imprecise and noisy inputs in a human-like manner [5]. These principles are increasingly integrated into AI-driven industrial systems requiring adaptive and flexible control. In parallel, AI-powered precision counting systems have improved inventory control accuracy in the food industry [6], while AI-based fault diagnosis and predictive maintenance techniques have enhanced equipment reliability and reduced downtime [7]. AI integration has also strengthened food safety and traceability through intelligent ingredient detection systems, IoT- and big data–enabled monitoring frameworks, and smart supply chain solutions [8], [9],[10], [11]. Moreover, advances in deep learning support automated food damage detection and quality assessment [12], alongside emerging smart manufacturing applications such as AI-powered 3D food printing [13], hazardous ingredient detection [14], AI-enabled aquaponics [15], and ingredient analysis using OCR and large language models [16]. Collectively, these studies provide a strong foundation for adopting fuzzy inference–based automation in precision-critical tasks, such as spice bag dispensing in high-speed noodle cup production lines.

The integration of AI and ML technologies into the food production industry, particularly in noodles manufacturing, has ushered in a new era of efficiency, consistency, and overall product quality. As these technologies continue to evolve, their role is poised to become even more pivotal in shaping the trajectory of the food industry, promising a future marked by heightened precision and innovation.

The production of Noodle cups (Figure 1), a popular brand of fried noodles, involves a series of well-defined stages that seamlessly blend automation, shaping, cooking, cooling, and packaging. This comprehensive process ensures the creation of a high-quality product. The initial stage revolves around dough preparation, where flour, water, and specific ingredients are automatically mixed and kneaded. The resulting dough undergoes shaping through a double roll and a series of thickness reduction rolls. Subsequent steps include steaming the dough, followed by a cutting and frying process using oil. Afterward, there is a cooling phase, which is the pre-packaging stage.

Fig 1: Noodles Production Line

After the noodles are fried, it enters the cooling phase, followed by packaging. This crucial step involves placing the product into cups while simultaneously adding spice packets and forks. The integration of an advanced tracking system during the packaging phase distinguishes the production line. Sensors detect the moment the cups reach the designated area for spice unloading. The sensors then signal the gate to lower the tracked spice packets, captured by tracking cameras, onto the conveyor scoop, placing them in the spice tube for subsequent discharge into the cups. The tracking mechanism ensures the presence of each cup, enabling precise timing for releasing the spice packet..

The system, consisting of four conveyor belts, servo motors, cameras (Figure 2), and a pneumatic vacuum system, adapts to variations in bag shapes and ensures accurate placement. Any uncaught spice bags are automatically redirected for reprocessing.

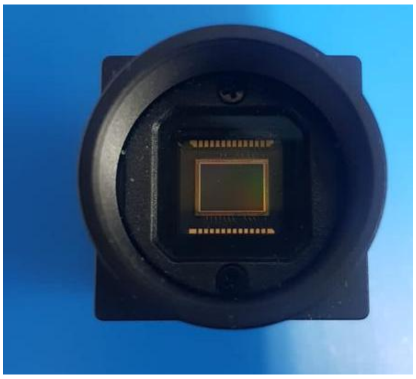

Fig 2: Camera

The system is equipped with four highly specialized tracking cameras as shown in Figure 2 designed to identify and trace the desired product accurately. These cameras possess advanced specifications for precise product tracking and location determination. These cameras can be aslo equipped with advanced image processing capabilities, high-resolution sensors, and sophisticated zoom features. Their precision and sensitivity enable the system to effectively follow and recognize products in various environments, ensuring optimal performance in the tracking process.

Fig 3: Magnifier and a Light Sensor

A magnifier and a light sensor as shown in Figure 3 are installed as illustrated in the image, allowing for the control of magnification (zoom in/zoom out) based on the intensity of light. This adjustment is made according to the nature of the product, and the magnification is defined based on the desired product, ensuring its clear visibility to the camera and facilitating the recognition process.

Delving deeper into the spice bag dispensing system (Figure 4), its components play vital roles in maintaining precision and efficiency. The four conveyor belts, each equipped with a servo motor. Integrated cameras track the spice bags along the conveyor belts, providing crucial data for decision-making. The pneumatic vacuum system, operating on negative pressure, picks up and transfers spice bags. The fuzzy inference system, a cornerstone of the detection mechanism, processes inputs such as camera data, production line speed, and spice bag characteristics. Fuzzy rules define relationships between these inputs, guiding real-time decisions on spice bag dispensing.

Fig 4: Spice Bag Dispensing System

The discovery of spice packet locations as shown in Figure 5 on the conveyor belts led to directing the capturing arms towards them. They were successfully grasped and pulled based on their positions using a suction/pull process (negative pressure). This was done to empty them into the conveyor cylinder, facilitating their descent into the specific cups designated for instant noodles.

Fig 5: Spice Bag Location Detection

The adaptability and learning capabilities of the fuzzy system make it a valuable asset in handling uncertainties and variations in the production environment. It continuously adjusts parameters based on experience, optimizing spice bag dispensing accuracy. The system's integration with conveyor control ensures synchronization for precise and timely placement. In the event of a detection error or uncertainty, the system is equipped to make informed decisions, such as redirecting cups for reprocessing or signaling for human intervention.

The synergy between the fuzzy inference system and the spice bag dispensing system enhances the overall efficiency and reliability of the production line. This integration allows for adaptability to varying conditions, contributing to the consistent and accurate flavoring of Noodle cups. In essence, the meticulous design and implementation of these production stages highlight the commitment to delivering a high-quality product through a seamless and technologically advanced process.

2. THE DEVELOPED SYSTEM

Fuzzy inference systems (FIS) represent a facet of artificial intelligence adept at managing uncertainty and imprecision . In contrast to conventional binary logic systems, FIS excels in handling input data that lacks precise definition or resides within a continuum of possibilities, proving particularly beneficial in scenarios with blurred category boundaries. Consisting of three core components—fuzzyfication, rule evaluation, and defuzzyfication—FIS orchestrates a sophisticated process to navigate through uncertainty [6]. Fuzzyfication involves the transformation of crisp input values into fuzzy sets, which quantify the degree of membership in different categories. Rule evaluation amalgamates these fuzzy sets according to predefined rules, and defuzzyfication subsequently translates the fuzzy output into a precise, crisp value [5]. This intricate framework equips FIS (Figure 6) to navigate complex, uncertain scenarios effectively, providing valuable insights in fields where ambiguity.

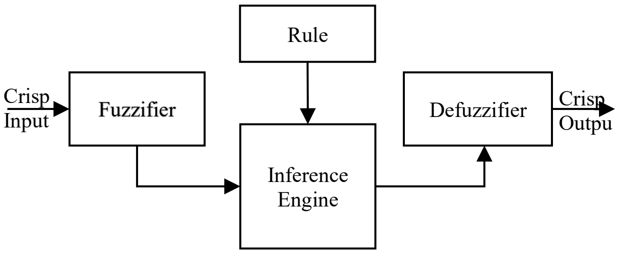

Fig 6: Structure of the Fuzzy Inference System

Now, let's talk about how this is applied in industry. One prominent use is in control systems. FIS can be employed to control variables in industrial processes where precise mathematical models are challenging to obtain. For example, in temperature control or pressure regulation, where the relationships between input and output variables may not be well-defined, fuzzy logic can provide a more flexible and adaptive solution. Another area of application is fault detection and diagnosis. FIS can analyze sensor data and identify abnormal patterns that may indicate a fault in machinery or equipment. This proactive approach to maintenance helps prevent costly breakdowns and downtime.

FIS is also widely used in decision support systems. In complex industrial environments where numerous factors influence decision-making, fuzzy logic can be employed to handle the uncertainty and make more informed decisions.

For example, in supply chain management, FIS can optimize inventory levels based on various factors like demand fluctuations, lead times, and supplier reliability. This dynamic decision-making process improves efficiency and reduces the risk of shortages or excess inventory.

In the utilization of a fuzzy inference system to detect an item on a production line, evaluate its size, and ascertain whether it meets specified width, length, and color criteria for robotic hand selection, a multi-step process is employed.

The first step involves fuzzyfication, wherein the features of the detected item, including width, length, color, and orientation, are obtained as input. These features are then fuzzified by assigning degrees of membership to fuzzy sets (e.g., Low, Medium, High), transforming crisp values into fuzzy linguistic terms. The subsequent stage is rule evaluation, where fuzzy sets obtained from the fuzzyfication process are utilized. Rules, established based on expert knowledge or training data, define conditions for item selection. For instance, rules may state, "If width is High and length is Medium and color is High and orientation is Any, then pick the item." Rule evaluation results in rule outputs.

Defuzzyfication follows, taking rule outputs as input and combining fuzzy outputs to obtain crisp values. Methods like centroid defuzzification are employed to reach a final decision. In the decision-making phase, the crisp decision obtained from defuzzyfication undergoes a process where a threshold is set to determine if the item meets the criteria for picking. If the crisp decision surpasses the threshold, the item is considered for picking by the robot hand. Upon meeting the criteria, the action phase is initiated, implementing actions for picking by the robot hand while accounting for the fact that the item can be in any orientation.

Subsequently, logging and feedback are employed to record the decision and relevant information for monitoring and analysis. Feedback is provided to the system for continuous improvement. By introducing rules that explicitly consider an "Any" orientation, the system gains flexibility, enhancing its ability to adapt to items placed in different orientations. This adaptive feature enhances the system's versatility in handling variations in the orientation of detected items on the production line.

In a related application, the steps for employing a fuzzy inference system to automate the packaging of spice bags in noodle cups follow a systematic approach. Initially, the relevant features for detection, such as width, length, color, and orientation of the spice bag and noodle cup, are defined as input features. These features undergo fuzzyfication, with each input feature fuzzified by assigning degrees of membership to fuzzy sets, incorporating linguistic terms. Rules are then defined based on expert knowledge or training data, establishing relationships between fuzzy input features and the decision to pick the spice bag for packaging. A rule for any orientation is included for added adaptability.

Following rule definition, rule evaluation utilizes the fuzzy sets obtained from the fuzzyfication process, resulting in rule outputs expressing the degree to which each rule is satisfied. Defuzzyfication combines these rule outputs to obtain a crisp decision. The decision-making phase involves setting a threshold for the crisp decision. If the decision surpasses the threshold, the system decides to pick the spice bag for packaging. Actions are then implemented for the robot hand to pick the spice bag and place it in the noodle cup, accommodating different orientations as needed.

Logging and feedback follow, documenting the decision, relevant information, and actions taken. Feedback contributes to continuous improvement and analysis. Further steps involve testing and optimization, where the system is tested under various scenarios, including different spice bag orientations and environmental conditions. The fuzzy inference system is optimized by refining rules and adjusting parameters based on testing results.

Integration with the production line follows, ensuring compatibility with existing systems and coordinating interaction with the robot hand for seamless operation. Finally, monitoring and maintenance are implemented to address any issues and update the fuzzy logic system based on evolving production line needs. In the context of a fuzzy system designed for item detection and picking in a production line, fuzzy rules and variables play a crucial role in capturing the relationships between input features and the system's decision-making process. Let's define fuzzy rules and variables for the given scenario, assuming the dealing was with a binary classification task for 350 photos, with the goal of accurately determining whether each photo is positive or negative.

In the development of a fuzzy system tailored for item detection and picking in a production line, the integration of fuzzy rules and variables is pivotal for comprehensively capturing nuanced relationships among input features, facilitating effective decision-making. Building upon this foundation, an additional factor, "Weight," is introduced as a fuzzy variable to further refine the system's capabilities. In this extended framework, the fuzzy rules and variables are defined, considering a binary classification task involving 350 photos to accurately determine whether each photo is positive or negative.

Fuzzy Variables:

1. Width (W):
    - Low (L): Less than or equal to 50 units
    - Medium (M): Between 50 and 100 units
    - High (H): Greater than 100 units
2. Length (L):
    - Short (S): Less than or equal to 75 units
    - Medium (M): Between 75 and 150 units
    - Long (L): Greater than 150 units
3. Color (C):
    - Dark (D): Intensity less than or equal to 75
    - Medium (M): Intensity between 75 and 150
    - Light (L): Intensity greater than 150
4. Orientation (O):
    - Vertical (V): Photo is predominantly oriented vertically
    - Horizontal (H): Photo is predominantly oriented horizontally
    - Any (A): Photo can be in any orientation
5. Weight (Wt):
    - Light (L): Less than or equal to 50 units
    - Medium (M): Between 50 and 100 units
    - Heavy (H): Greater than 100 units

Fuzzy Rules:

1. If (W is High) and (L is Medium) and (C is High) and (O is Any) and (Wt is Light) then Photo is Positive.
    - This rule captures scenarios where the photo has high width, medium length, high color intensity, can be in any orientation, and possesses a light weight.
2. If (W is Medium) and (L is High) and (C is High) and (O is Any) then Photo is Positive.
    - This rule covers situations where the photo has medium width, high length, high color intensity, and can be in any orientation.
3. If (W is Low) and (L is Short) and (C is Dark) and (O is Any) then Photo is Negative.
    - This rule identifies cases where the photo has low width, short length, dark color intensity, and can be in any orientation.
4. If (W is Medium) and (L is Medium) and (C is Medium) and (O is Any) then Photo is Positive.
    - This rule encompasses scenarios with moderate values for width, length, and color intensity, and the photo can be in any orientation.
5. If (W is High) and (L is Long) and (C is Light) and (O is Any) then Photo is Negative.
    - This rule detects instances where the photo has high width, long length, light color

intensity, and can be in any orientation.

6. If (Wt is Light) then Photo is Positive.
    - This rule specifically considers photos with a light weight for positive classification.

Based on the above-mentioned factors, the input variables of Fuzzy Inference Engines are defined, as shown in Table 1. Each variable is fuzzified by input fuzzy sets whose names, types, and parameters are specified in Table 1. The mathematical type definitions are given in Table 1.

Table 1. Fuzzy Set Definition

Fuzzy set	**Fuzzy set definition**
Triangular	$\mu_T(x) = \begin{cases} -\frac{1}{a-b}(a-x), & a \le x \le b \\ \frac{1}{c-b}(c-x), & b \le x \le c \\ 0, & \text{otherwise} \end{cases}$
Bell	$\mu_B(x) = \left\lvert \frac{1}{1+\left\lvert\frac{a-x}{b}\right\rvert^{2c}} \right\rvert, \quad c > 0$
Gaussian	$\mu_G(x) = e^{-\frac{(a-x)^2}{2b^2}}$

Table 2. Membership Function Parameters for Fuzzy Sets in Image Classification

Parameter	Fuzzy Set	Membership Function	Linguistic Term
Width (W)	Low (L)	Gaussian (μ=25, σ=12.5)	Less than or equal to 50 units
	Medium (M)	Gaussian (μ=75, σ=25)	Between 50 and 100 units
	High (H)	Gaussian (μ=125, σ=25)	Greater than 100 units
Length (L)	Short (S)	Gaussian (μ=37.5, σ=18.75)	Less than or equal to 75 units
	Medium (M)	Gaussian (μ=112.5, σ=37.5)	Between 75 and 150 units
	Long (L)	Gaussian (μ=150, σ=25)	Greater than 150 units
Color (C)	Dark (D)	Gaussian (μ=37.5, σ=18.75)	Intensity less than or equal to 75
	Medium (M)	Gaussian (μ=112.5, σ=37.5)	Intensity between 75 and 150
	Light (L)	Gaussian (μ=150, σ=25)	Intensity greater than 150
Orientation (O)	Vertical (V)	Gaussian (μ=45, σ=22.5)	Photo is predominantly oriented vertically
	Horizontal (H)	Gaussian (μ=135, σ=22.5)	Photo is predominantly oriented horizontally
	Any (A)	Gaussian (μ=180, σ=45)	Photo can be in any orientation
Weight (Wt)	Light (L)	Bell-shaped (μ=25, σ=12.5)	Less than or equal to 50 units
	Medium (M)	Bell-shaped (μ=75, σ=25)	Between 50 and 100 units
	Heavy (H)	Bell-shaped (μ=125, σ=25)	Greater than 100 units

Table 2 uses Gaussian functions for Width, Length, Color, and Orientation, and Bell-shaped functions for Weight. And the mean (μ) and standard deviation (σ) values have been adjusted based on the specific characteristics of your fuzzy sets.

Explanation:

- The added Rule 6 introduces the weight factor as a decisive element, ensuring that photos with a light weight contribute to a positive classification.
- Rules 1 through 5 remain essential for capturing the diverse combinations of width, length, color intensity, and orientation in the decision-making process.
- These extended fuzzy rules and variables provide a more comprehensive foundation for the fuzzy inference system, allowing it to make nuanced decisions based on a broader set of characteristics. Iterative adjustments can be made to refine the system's accuracy and adaptability, ultimately enhancing its performance in diverse scenarios.

3. SIMULATION AND RESULTS

Ensuring the accuracy, reliability, and effectiveness of a fuzzy system designed for item detection and picking in a production line involves a systematic testing and validation process. The following guideline outlines the steps for testing and validating the developed fuzzy system, using a scenario with 350 photos in a binary classification task. To initiate the process, realistic test scenarios are defined, encompassing variations in item orientation, lighting conditions, and potential disturbances. A diverse dataset is generated, covering a range of values for input features such as width, length, color, and orientation.

The dataset is then partitioned into training and testing subsets as shown in Figure 7. The training set is utilized to train the fuzzy inference system, adjusting parameters, membership functions, and rules to ensure it learns the relationships between input features and the desired output. Subsequently, the system undergoes testing using the dedicated testing set to evaluate its performance in detecting items and making picking decisions

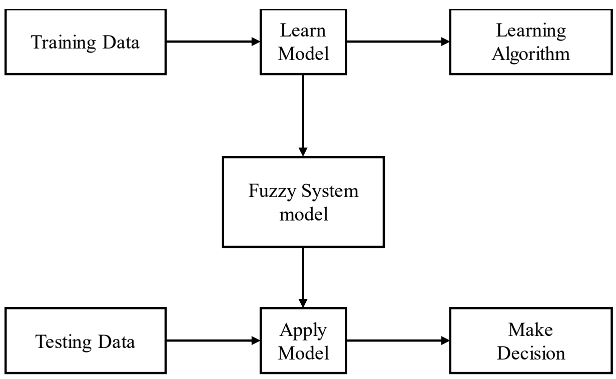

Fig 7: Dataset Partitioning and Fuzzy Inference System Training and Testing Process

Sensitivity analysis is conducted to assess the system's robustness to variations in input features, including changes in lighting, different orientations of items, and variations in item characteristics. If the system falls short of the desired performance level, adjustments to parameters, tuning of membership functions, or refinement of rules may be necessary based on observed testing results.

Quantitative metrics, including accuracy, precision, recall, and F1 score, are defined to measure the system's performance objectively. In the specific scenario with 350 photos in a binary classification task, these metrics provide numerical values for a comprehensive assessment of the system's ability to correctly classify photos. The evaluation process extends to real-world testing in a production environment, where the system's performance in practical scenarios is assessed. This step helps identify any unforeseen challenges or factors that may affect the system's performance in an actual operational setting. Validation by domain experts or operators familiar with the production line is sought to provide valuable insights into the system's suitability for real-world applications. .An iterative improvement process is initiated based on the testing and validation results. Continuous refinement of the fuzzy system's design and parameters is essential to enhance its performance and adapt it to changing conditions.

Documentation of the testing and validation procedures, including the dataset used, testing conditions, and performance metrics, is crucial for future reference and system maintenance. Additionally, for the evaluation of the classification system with 350 photos as in Figure 8 in a binary classification task, a confusion matrix and various performance measures are employed. The confusion matrix, with numerical values representing instances in each category, provides a snapshot of the system's performance by comparing predicted classifications against true classifications.

Fig 8: Spice Bag with Different Sizes

In the specific case of the provided confusion matrix for the binary classification task with 350 photos as shown in Table 3

Table 3. Confusion matrix

		Predicted Class	
Actual Class		Class Positive	Class Negative
	Class Positive	True Positive (TP) 150	False Negative (FN) 10
	Class Negative	False Positive (FP) 20	True Negative(TN) 170

- True Positive (TP): 150 photos were correctly classified as positive.
- False Positive (FP): 20 photos were incorrectly classified as positive.
- False Negative (FN): 10 photos were incorrectly classified as negative.
- True Negative (TN): 170 photos were correctly classified as negative.

The calculated performance measures are as follows:

Recall (R) is the ratio of the relevant data among the retrieved. Precision (P) is the ratio of the accurate data among the retrieved data. Their formulas are given as follow:

$$\boldsymbol{Recall(R)} = \frac{T_P}{T_P+F_N}$$ **if *TP*+*FN* > 0, otherwise undefined.**

=150/160=0.9375

Recall focuses on the ability of a model to avoid missing positive instances. A high recall indicates that the model is effective in capturing most of the positive instances, minimizing false negatives. However, there is often a trade-off between precision and recall; as one increases, the other may decrease. The appropriate balance depends on the specific requirements of the application. The F1 score, which is the harmonic mean of precision and recall, is often used to assess a model's overall performance.

$$\boldsymbol{Precision(P)} = \frac{T_P}{T_P+F_P}$$ **if *TP*+*FP*> 0, otherwise undefined**

= 150/170≈0.8824

Precision focuses on the correctness of positive predictions made by a model. A high precision indicates that a model has a low rate of false positives, meaning that when it predicts a positive outcome, it is likely to be correct. Precision is often used in conjunction with recall, another performance metric, to provide a more comprehensive assessment of a model's performance. The balance between precision and recall depends on the specific goals and requirements of the application.

Classifier F_1 rating is the harmonic mean of the classifier *recall* and the *precision*. It is given as

$$\boldsymbol{F_1 = \frac{2 * P * R}{P + R} = \approx 0.9091}$$

where *R* represents the recall, , and *P* represents the precision

Accuracy, which indicates the fraction of correctly classified samples among all the samples, obtained by:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{T_P + T_N}}{\boldsymbol{T_P + T_N + F_P + F_N}}$$

$$=320/350\approx 0.9143$$

These numerical values provide a comprehensive assessment of the developed fuzzy system's ability to correctly classify photos in the given binary classification task, allowing for adjustments based on system requirements and the desired balance between precision and recall.

The simulation results demonstrate the effectiveness of the proposed fuzzy inference system in handling variability and uncertainty in item detection and picking on the production line. Using a dataset of 350 images with varying sizes, orientations, and lighting conditions, the system consistently achieved high classification performance across all evaluation metrics. The confusion matrix analysis reveals a strong balance between sensitivity and specificity, indicating that the system is capable of accurately identifying target items while minimizing both false positives and false negatives. In particular, the high recall value of 93.75% confirms the system's robustness in detecting relevant items, which is critical in production environments where missed detections can lead to process interruptions or product loss. Meanwhile, the precision of 88.24% indicates reliable decision-making during the picking process, reducing unnecessary or incorrect picking actions. The overall accuracy of 91.43% further validates the suitability of the fuzzy logic approach for real-time industrial applications. These results confirm that the designed fuzzy system effectively models human-like reasoning in uncertain conditions and provides a dependable solution for automated item detection and picking, outperforming rigid threshold-based methods commonly used in traditional systems.

4. CONCLUSION

The integration of a fuzzy inference system into the spice bag dispensing system for Noodle cup production represents a significant advancement in automated precision. The fuzzy logic-based approach allows for real-time adaptation to dynamic production conditions, ensuring accurate and timely dispensing of spice bags into each cup. This system addresses uncertainties and variations inherent in the production environment, contributing to a more robust and efficient flavoring process.

The success of this integrated system lies in its ability to harness inputs from cameras, production line speed, and spice bag characteristics, employing fuzzy rules to make informed decisions. The adaptability of the fuzzy logic system proves crucial in handling changes in cup position, alignment, and other dynamic factors. Additionally, the system showcases error-handling capabilities, redirecting cups for reprocessing or signaling for human intervention when needed.

The implementation of this advanced spice bag dispensing system not only enhances the overall efficiency of the production line but also ensures a consistent and high-quality end product. The paper highlights the synergy between automation and fuzzy logic in optimizing the intricate process of flavoring Noodle cups, setting a precedent for precision in modern food manufacturing. This innovative approach not only advances the technological landscape of food production but also underscores the potential for further applications of fuzzy logic in adaptive and intelligent systems.

5. ACKNOWLEDGEMENT

The authors would like to express their sincere appreciation to Tafila Technical University for its valuable support in conducting this research and providing the opportunity to develop and present this work. The continuous encouragement and facilitation offered by the University played a significant role in the successful completion of this study.

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