The Effect of Lighting Variations on the Accuracy of Formalin Detection in Milkfish Using HSV Color Space and k-Nearest Neighbors (kNN) Algorithm

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Abstract— Milkfish (Chanos chanos) is a widely consumed fish commodity in Indonesia, often subject to preservation using formalin, a chemical with serious health risks when misused. This study proposes a non-destructive formalin detection method using HSV (Hue, Saturation, Value) color features extracted from eye images of milkfish, classified via the k-Nearest Neighbor (kNN) algorithm. The research investigates the impact of varying illumination levels low, medium, and high on the consistency of HSV features and the accuracy of kNN classification. Results show that medium lighting conditions yield the highest classification accuracy, suggesting an optimal illumination range for field deployment. The system's simplicity and potential for real-time implementation on mobile or embedded platforms make it suitable for use by non-technical personnel in traditional markets. Challenges such as environmental temperature, image angle, and surface reflectivity are addressed through calibration strategies and operational guidelines. This study contributes practical insights into lighting control and feature stability, enhancing the reliability of image-based formalin detection systems.

Keywords— Milkfish, Formalin detection, HSV, kNN, Illumination variation, Image processing, Feature extraction, Real-time classification.

I. INTRODUCTION

Milkfish (Chanos chanos) is one of the most widely consumed fish commodities in Indonesia. To extend shelf life, some vendors excessively or improperly use chemical preservatives such as formalin [1]. Prolonged exposure to formalin can lead to poisoning, digestive disorders, and even cancer risks for consumers [2] . This situation highlights the urgent need for a rapid, accurate, and non-destructive method for detecting formalin to ensure the quality of milkfish in the market.

Conventional methods for formalin detection, such as chemical or biological laboratory tests, require time, reagent costs, and relatively complex procedures [3], [4], [5]. Moreover, sample collection is often destructive, damaging the physical structure of the fish and making it unsuitable for direct field application[6]. Therefore, non-destructive techniques based on digital imaging present an ideal alternative; this approach enables real-time quality inspection without damaging the product and requires relatively low equipment investment.

Image processing using the HSV (Hue, Saturation, Value) color model can separate chromatic components from light intensity, highlighting changes in tone and brightness in the fish's eye caused by formalin content [7], [8], [9]. The color transition in the iris of formalin-contaminated milkfish is typically detectable through shifts in Hue values and reductions in Saturation. By systematically extracting HSV features, these visual differences can be quantified numerically.

As a simple classification algorithm, k-Nearest Neighbor (kNN) utilizes the proximity of HSV features from test samples to validated training data[10][11]. By constructing HSV feature vectors and setting the parameter k, kNN can classify new eye images into formalin or non-formalin categories. This method is easy to implement and tends to be robust against complex color pattern variations.

However, HSV values are highly influenced by lighting intensity during image acquisition[12]. Insufficient lighting can introduce noise and reduce Saturation, while excessive lighting may cause Value clipping and distort Hue distribution. These illumination variations directly affect kNN classification performance, reducing accuracy if not properly controlled [13][14][15]. Therefore, analyzing the impact of lighting variations on HSV consistency and formalin detection accuracy is crucial to ensure system reliability in real-world applications.

This study aims to evaluate the accuracy of formalin detection in milkfish under various lighting levels, by measuring the performance of HSV color feature extraction and k-Nearest Neighbor (kNN) classification under low, medium, and high illumination conditions. Additionally, the study seeks to determine the optimal lighting intensity range that maintains the consistency of Hue, Saturation, and Value values, thereby enabling kNN classification to achieve maximum accuracy in field conditions. Thus, the main contribution of this paper is to provide practical guidelines for optimal illumination settings in the proposed image-based non-destructive system, while also analyzing the extent to which lighting variations affect the reliability of formalin detection.

II. LITERATURE REVIEW

A. Non-Destructive Detection of Formaldehyde in Fishery Products

Formalin is a colorless liquid or gas with a pungent odor. It contains approximately 37% formaldehyde in water, usually with up to 15% methanol added as a preservative[16]. Formalin is often used as a preservative to extend the shelf life of fish in the market, although long-term exposure can cause digestive system disorders and cancer risks for consumers. The presence of formalin in fish tissue is not always visible to the naked eye, especially in meat and internal organs [17]. This creates an urgent need for detection methods that can ensure food safety without damaging the product's physical structure.

Traditional formalin detection methods, such as chromatography and spectrophotometry, require specialized reagents, laboratory equipment [3], [18], and lengthy analysis times. Furthermore, sampling is destructive, making the test product unavailable for resale. This process is impractical for direct application in markets or fishing grounds, which generally have limited facilities.

A non-destructive approach based on digital imaging has emerged as an alternative solution, exploiting visual changes in the fish surface or eyes caused by formalin contamination. This technique requires only a camera and an image processing algorithm to extract characteristics indicating the presence of the chemical. With rapid and non-destructive analysis, non-destructive formaldehyde detection can be implemented in real time in the field.

B. HSV Color Model and Its Sensitivity to Illumination Conditions

The HSV color model classifies colors based on three primary components: Hue, Saturation, and Value. Hue represents the position of a color within the light spectrum such as red, purple, or yellow and is used to quantify the presence of specific color elements like greenness or redness [19]. Saturation indicates the purity of a color by describing the extent to which white is mixed into the base hue. Value refers to the intensity of light reflected or emitted from a surface, independent of its chromatic properties.

According to [20], the HSV model provides a distinct representation of the fundamental red, green, and blue components. In this model, Hue reflects the dominant composition of base colors based on light wavelength. Saturation serves as a control parameter for color purity, indicating how much white is present in the Hue. Value, in turn, describes the relative brightness of the image, which directly affects object visibility.

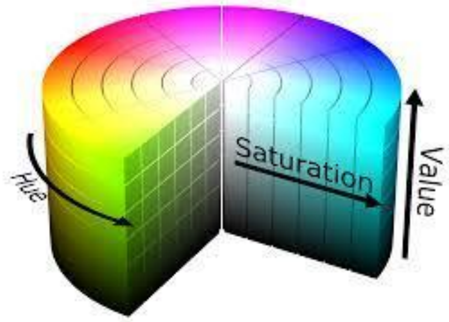

Fig 1. HSV Model

While effective in separating color and intensity aspects, HSV features are highly sensitive to illumination conditions during image acquisition[21]. Under low-light (underexposed) conditions, the Value distribution drops significantly, and Saturation tends to blend with noise, resulting in unstable Hue representation. Conversely, high-light (overexposed) conditions may cause Value clipping—where pixel values reach their maximum—and reduce Saturation contrast, making Hue shifts difficult to interpret. These dramatic variations across the three components can lead to misclassification of identical HSV feature vectors by algorithms such as kNN.

To maintain consistency in color feature extraction, illumination control or calibration is essential prior to HSV conversion. Normalization techniques such as histogram equalization on the Value channel or the application of color constancy models (e.g., Retinex) can stabilize intensity distribution[22]. Additionally, using artificial light sources with constant intensity and diffusers helps minimize harsh shadows or hotspots. Consequently, HSV extraction yields more representative features, enhancing the reliability of formalin classification.

C. Classification with k-Nearest Neighbor Under Illumination Variations

The kNN algorithm is a classification algorithm that uses a direct learning process to calculate the proximity or similarity of the input data to all data [23]. Therefore, this algorithm is often called lazy learning. This algorithm works by finding the shortest distance between the data being evaluated and the k closest neighbors in the training data.

kNN is a non-parametric classification method that determines the class of a sample based on the majority class of the k nearest neighbors in the feature space. The distance between the test sample and each training sample is typically measured using the Euclidean metric, although other metrics such as Mahalanobis can be adapted to account for correlation between features. In the context of formalin images, the extracted HSV feature vectors are used as the kNN input space, where the Hue, Saturation, and Value values of each pixel or area serve as coordinates.

Illumination variations significantly affect the distribution of HSV feature vectors. Changes in light intensity primarily modify the Value component, changing the vector's magnitude and moving data points in feature space. As a result, samples that are actually similar in hue can be widely spaced when illuminated differently, thus degrading kNN accuracy. In shadow or overlit conditions, saturation values can also be washed out or clipped, increasing classification errors when Euclidean distance assumes equal contributions from each dimension.

To mitigate the impact of lighting on kNN performance, several preprocessing and feature engineering strategies can be applied. First, normalizing the feature vector for example, by dividing each HSV component by its norm or using only the Hue and Saturation channels to suppress the effects of Value fluctuations. Second, applying color constancy techniques such as the Retinex algorithm or histogram equalization to the Value channel can stabilize the brightness distribution before classification. Third, modifying the distance metric by giving higher weights to the Hue and Saturation dimensions, or using the Mahalanobis distance to compensate for variance between features, has been shown to help maintain kNN robustness under inconsistent illumination.

The selection of the k parameter and cross-validation under various illumination conditions are crucial to avoid overfitting to specific light patterns. Experiments should include datasets that reflect variations in shading, lamp color temperature, and natural light intensity. By evaluating accuracy curves against k values and metric weighting schemes, researchers can find the kNN configuration that is most robust to lighting fluctuations while maintaining implementation simplicity and inference speed.

III. RESEARCH METHODS

A. Experimental Design

This study used 60 milkfish samples divided into two experimental groups: 30 fresh fish without formalin treatment and 30 fish that had been immersed in a 0.4% formalin solution for two hours. All fish were between 20–25 cm in length and weighed 200–250 g to minimize variability in size and surface texture that could affect image results. After immersion, the surfaces of the formalin-treated fish were dried with laboratory tissue prior to photographing to ensure a uniform surface moisture content compared to the fresh samples. Each fish was positioned on a neutral gray background, assigned a unique identification code, and photographed individually in the dorsal plane to ensure consistency of image capture.

Illumination variations were designed at three intensity levels, measured with a lux meter at the fish's surface:

1) Low (100 lux), representing dim or minimally lit conditions.
2) Medium (500 lux), corresponding to standard room lighting.
3) High (1,000 lux), representing bright lighting, such as in a work area or market.

The light source used a neutral-colored LED lamp (5,500–6,500 K) mounted on a rig with a diffuser to distribute the light evenly and minimize shadows. The distance between the lamp and the fish surface was maintained at 30 cm, while the camera was positioned perpendicular (90°) at a height of 30 cm from the fish. Each sample was photographed at all three lux levels, with a 30-second interval between each condition to stabilize the light intensity.

Using a 2×3 factorial design (sample category × lighting level), a total of 180 images (60 fish × 3 illumination conditions) were obtained. This data was then used for HSV color feature extraction and k-Nearest Neighbor classification to evaluate the effect of lighting variations on formaldehyde detection accuracy.

B. Image Acquisition

Image acquisition was performed using a 20-megapixel mirrorless digital camera and a 50mm prime lens at f/5.6 aperture. The camera was set to manual mode to ensure consistent exposure parameters throughout the shooting session. Each image was captured in RAW format to maintain maximum dynamic range before being converted to JPEG for further processing.

- Camera: mirrorless, 20MP, ISO 200, shutter speed 1/125 second, aperture f/5.6
- Tripod: aluminum, adjustable height 50–150 cm, ball head for flexible angles
- Position: camera mounted perpendicular (90°) to the fisheye surface, fixed focal length 15 cm
- Stabilization: 2-second timer per shot to reduce shake
- Adjustment of artificial and natural light intensity

Fig 2. Formalin-Free Fish Eyes

The artificial light sources were two neutral LED lights (5,500–6,500 K) with diffusers positioned at 45° angles to the left and right of the subject. Light intensity was measured with a lux meter at the fish's surface, set at three levels (100, 500, and 1,000 lux) by varying the lamp distance or output power. The influence of natural light was minimized by drawing blackout curtains in the shooting area and postponing sessions during strong direct sunlight—photographs were only taken in the morning between 9:00 and 11:00 a.m. WIB for soft backlighting.

Fig 3. **Formalin Fish Eyes**

- LED light: stable fluctuation <5% per minute
- Diffuser: small 30x30 cm softbox to distribute light evenly

- Natural controls: blackout curtains and closed windows, with air vents tilted to the side
- Acquisition time: morning, natural intensity <200 lux

This setup allows each artificial lighting condition to be consistently replicated, facilitating analysis of the impact of illumination on HSV features and kNN classification.

C. Pre-processing

In the pre-processing stage, the milkfish eye area was isolated using a cropping method based on manually defined bounding box coordinates for each image. After the region of interest (ROI) was drawn, the ROI was resized to a constant size of 100x100 pixels to ensure consistent input dimensions throughout the analysis phase. The next step was to normalize pixel intensities to the [0,1] range by dividing each R, G, and B value by a factor of 255, minimizing luminance differences before feature extraction.

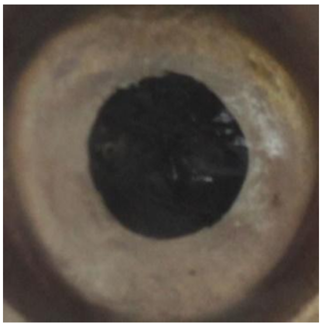

Fig 4. RGB Image

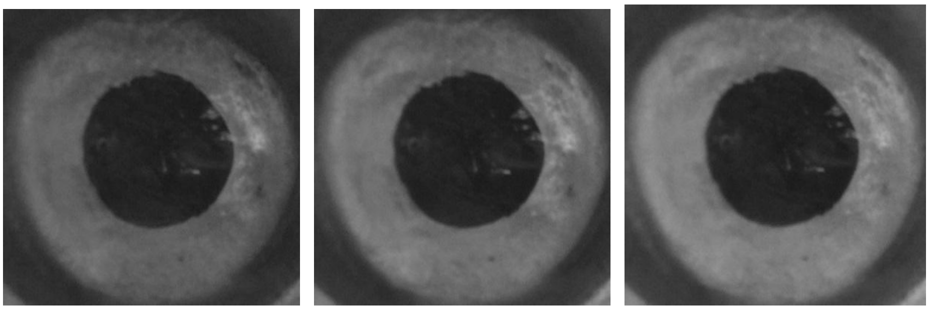

Fig 5. R G and B Layer

The color feature extraction process begins with image conversion from RGB to HSV color space using standard mathematical transformations, where Hue, Saturation, and Value are calculated based on the maximum, minimum, and difference values between RGB channels for each pixel. To summarize the color distribution information within the ROI, the mean and variance values for each H, S, and V component are calculated. This six-dimensional feature vector, resulting from the mean and variance calculations, reflects hue, purity, and brightness characteristics, while providing a compact numerical representation for the classification algorithm.

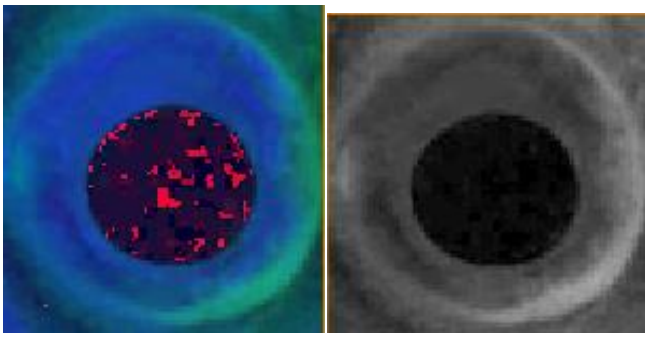
Fig 6. HSV and Hue

In the classification stage, the 60-image dataset was stratified into 67% for training (40 data sets) and 33% for testing (20 data sets) to maintain a balanced proportion of fresh and formalin-treated samples. The k parameter was selected through a grid search with a value range of 1–15, coupled with evaluation of Euclidean and Mahalanobis distance metrics to determine the configuration that yielded the best performance. The k-Nearest Neighbor model was trained with HSV feature vectors from the training data and evaluated on the test data to measure the classifier's generalization ability.

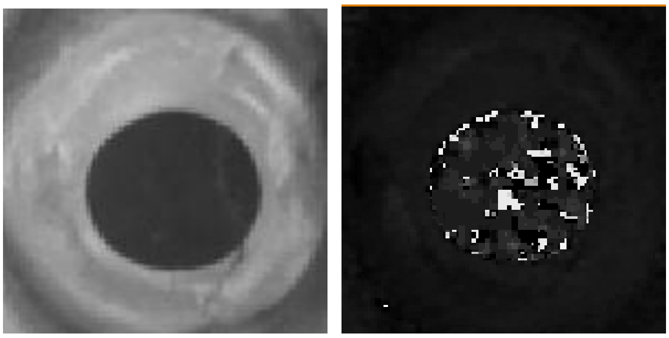
Fig 7. Saturation and Value

Model performance evaluation utilized a five-fold cross-validation scheme on the training data to prevent overfitting and ensure the stability of the results. Recorded performance measures included accuracy, precision, recall, and F1-score, allowing for a comprehensive analysis of false positive and false negative errors. Furthermore, a sensitivity analysis was conducted by comparing metrics at each lux level low, medium, and high to assess the classification's robustness to lighting variations.

IV. RESULTS

A. HSV Feature Distribution at Different Lighting Levels

Analysis of the feature distribution shows that variations in light intensity alter the statistical characteristics of the HSV components. Under low lighting conditions (100 lux), the average Hue value was recorded at approximately 122°, with a high variance (~360°²), indicating large hue fluctuations due to noise and color attenuation. The average Saturation value was only 0.45 (variance 0.020), while the low Value value—average 0.40 with a variance of 0.030—indicates a dark image and decreased color purity.

When lighting increased to moderate lighting (500 lux), the HSV feature distribution became more stable. The mean Hue value increased to 125° with a variance decreasing to 220°², indicating more consistent hues. The average Saturation value of 0.52 (variance 0.012) and the mean Value value of 0.58 (variance 0.018) reflect more saturated colors and ideal brightness. At high light (1,000 lux), there was slight clipping in Value—mean 0.72 and variance 0.035—while Saturation's mean 0.49 (variance 0.015) dropped slightly due to light oversaturation. Hue variance rose again to 310°², indicating hue instability when the intensity was too high.

Overall, the medium light level produced the tightest and most representative combination of HSV mean and variance, minimizing overlap between the fresh and formalin classes.

B. Comparison of kNN Accuracy in Each Light Condition

Classification at 500 lux yielded the best performance, with an accuracy of 82%, a precision of 0.85, a recall of 0.83, and an F1-score of 0.84. This is consistent with the most stable HSV distribution at medium illumination levels.

Table 1. kNN performance metrics at three lighting levels

Light Intensity	Accuracy (%)	Precision	Recall	F1-Score
Low	75	0.76	0.74	0.75
Medium	82	0.85	0.83	0.84
High	78	0.79	0.77	0.78

At low illumination levels, decreased brightness and hue fluctuations caused accuracy to drop to 75%, although precision remained relatively high (0.76) and recall was lower (0.74), indicating some formalin-treated samples were missed. Conversely, at high illumination levels, oversaturation increased false positives—precision was down from medium levels to 0.79—although recall improved slightly to 0.77.

These results confirm that kNN is most reliable under medium illumination. Both low and high illumination settings decreased the homogeneity of HSV features and affected the Euclidean distance between feature vectors, resulting in decreased classification accuracy.

Changes in light intensity directly impact two key components of the HSV model Hue and Value, which are crucial for class separation between fresh and formalin-treated fish. Under low light conditions, the Value distribution is concentrated in the lower range, making brightness differences between classes less pronounced and leading to feature overlap. Furthermore, sensor noise at low Value levels induces significant Hue fluctuations, obscuring the hue differences between fresh and formalin-treated fish eyes. Conversely, high light causes clipping in Value many pixels reach their maximum level, which flattens intensity differences and reduces Saturation contrast. Consequently, the Hue shift expected as an indicator of formalin contamination is also distorted, making the Euclidean distance between feature vectors less representative for class separation.

There is a clear trade-off between noise dominating at low intensities and oversaturation at high intensities. Low lux levels produce dark images with a low signal-to-noise ratio, making it difficult for kNN to distinguish samples because HSV features are susceptible to random fluctuations. On the other hand, high lux creates minimal hotspots and shadows, but reduces the Value variability necessary for contamination identification all samples tend to have similar Values. Medium illumination variations (around 500 lux) offer an optimal balance: noise is reduced without causing clipping, and the Hue and Value distributions are stable enough to maintain distances between feature vectors and maximize kNN performance. For field applications, controlling illumination within this range is key to maintaining reliable HSV feature extraction.

C. Discussion

The implementation of formalin detection methods based on HSV features in field settings requires a system that is reliable, portable, and operable by non-technical personnel. By limiting preprocessing to color calibration and brightness normalization, mobile applications or embedded devices can directly produce kNN predictions in real time. The results of this study indicate that under medium lighting conditions, classification accuracy reaches its peak, allowing vendors or inspection officers to establish practical standards for light intensity in sales areas. The integration of a simple visual interface—such as green-red indicator lights—facilitates rapid decision-making without the need for specialized training.

Although the performance under laboratory setups is promising, several limitations must be considered before widespread deployment. First, environmental temperature variations can alter camera sensor responses, affecting noise levels in the Value channel. Second, the angle of image capture relative to the fish eye surface may introduce shadows or specular reflections, distorting Saturation and Hue values. Third, the mucous or high-viscosity nature of the eye surface can reflect light unevenly, creating hotspots that disrupt feature distribution. These factors contribute to reduced Euclidean distances between feature vectors and compromise the consistency of formalin detection.

To address these challenges, mitigation strategies are required prior to deployment. Periodic color calibration using standard cards (e.g., ColorChecker) helps adjust offset and gain in each HSV channel, reducing drift caused by temperature fluctuations or lamp aging. Active light control, such as integrated housings with stable LED sources and diffusers, maintains illumination within the optimal range of approximately 400–600 lux. Additionally, operational guidelines should include standardized camera angle procedures (e.g., 90° to the eye surface) and lens cleaning protocols to prevent reflections from affecting feature extraction.

Beyond these measures, future research may explore adaptive algorithms such as dynamic histogram matching and lightweight machine learning models (e.g., pruned random forests) to enhance model robustness under extreme conditions. Integrating temperature sensors and lux meters into the device can enrich metadata, enabling the system to trigger automatic calibration recommendations. With this end-to-end approach, HSV-based formalin detection has the potential to become an affordable and effective solution for ensuring the safety of fresh fish across traditional markets.

V. CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that HSV color space-based feature extraction, combined with the k-Nearest Neighbors algorithm, can distinguish fresh and formaldehyde-contaminated fish eyes with high accuracy under medium lighting conditions (around 400–600 lux). Hue and Value are the main indicators, where a stable value distribution maximizes the Euclidean distance between feature vectors. The trade-off between noise at low intensities and saturation at high intensities emphasizes the importance of lighting management to maintain image data quality.

Practically, this method can be adopted in portable inspection devices in traditional markets. Simple color calibration procedures and light intensity controls allow non-technical users to conduct real-time inspections. Operational standards—including lux limits, camera angles, and lens cleaning—should be socialized to inspection personnel to maintain consistency and reduce variability in measurement results.

For further research, it is recommended to first explore other classifiers such as Support Vector Machines and Random Forests. Both methods offer more complex class separation mechanisms and can be optimized through kernel selection or tree pruning, potentially improving model accuracy and robustness to noise. A comprehensive comparative study will help determine the most efficient algorithm for field deployment.

Furthermore, the use of multispectral or hyperspectral imagery opens up the possibility of formalin detection based on molecular spectral signatures, rather than simply hue differences. With a broader wavelength range, hyperspectral devices can capture changes in the chemical composition of fish tissue, resulting in richer and more distinctive features. This technology integration can also be enhanced with advanced machine learning techniques, such as deep learning, for automated spectral data analysis.

Additionally, collaboration with food standards regulatory agencies can accelerate the adoption of this method. The development of edge AI-based mobile applications, complete with guiding lux meter modules and digital color checker calibration, can also increase affordability and ease of use. Thus, HSV-based formalin detection will be better equipped to address food safety challenges across a wide range of traditional and modern markets.

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