Milk Adulteration Detection Using Evaporation Residue Pattern Analysis and Convolutional Neural Networks

1st Kartik Baviskar
Department of Computer Engineering (R.L.)
Pimpri Chinchwad College of Engineering,
Pune, India
rbaviskar935@gmail.com

2nd Sujata Kolhe
Department of Computer Engineering (R.L.)
Pimpri Chinchwad College of Engineering,
Pune, India
sujata.kolhe@pccoepune.org

3rd Rohit Chavan
Department of Computer Engineering (R.L)
Pimpri Chinchwad College of Engineering,
Pune, India
rohitchavan114424@gmail.com

4th Suyog Chavan
Department of Computer Engineering (R.L.)
Pimpri Chinchwad College of Engineering,
Pune, India
chavansuyogy@gmail.com

5th Saurabh Gaikwad
Department of Computer Engineering (R.L.)
Pimpri Chinchwad College of Engineering,
Pune, India
saurabhgaikwad2004@gmail.com

***Abstract*: -The quality and safety of milk continue to be major areas of concern due to the numerous different substances that can be added to change nutritional content and physical properties. This paper presents a method for detecting adulteration in milk using an image processing framework to analyse evaporated milk residue from microscopic droplets and classify the resulting patterns with a convolutional neural network (CNN). All of the fresh milk used in the project was purchased from One of the Milk Centre in Akurdi, and samples with single adulterants were created by diluting water (10%, 20%, and 30%) and adding varying amounts of sugar (1 g-5 g), salt (1 g-5 g), and detergent (1 g-5 g). Approximately 5-10 µL of each droplet was placed on a glass slide for evaporation at controlled conditions to produce residue morphologies that correlate to solute transport and crystallization, as well as the flow of the liquid through air and glass interfaces. An optical microscope was used to take a full image as well as 3 images from the edge of each droplet and 3 images from the center while keeping the light and magnification constant. The resulting images were then labeled by the type of adulterant and concentration level and were processed using grayscale conversion, segmentation, and residue pattern extraction prior to pass-through CNN. The proposed framework combines low-volume experimentation, microscopy, image processing, and deep learning into a single detector for adulterants. This CNN model achieved a general success rate of around 89% at classifying the test data. The matrix statistics clearly indicate that classes appear distinct for the most part; the majority of the contaminant classes were properly recognized. There were, however, some confusion between the sugar and pure milk, as well as between the water and salt, due to their high similarity in the appearance of their residues.**

Keywords: milk adulteration, evaporation residue, dried droplet pattern, microscopy, image processing, convolutional neural network, food quality detection.

I. INTRODUCTION:

Due to rising demand and economic incentives, milk adulteration has become a serious concern when it comes to food safety. Common adulterants found in milk include water, sugar, salt, and detergents [1]-[4]. Conventional methods of detecting these additions are often time-consuming, costly, and require laboratory facilities through the use of chemical or spectroscopic methods [5], [6]. As a result, there is a strong need for rapid, inexpensive, and image-based detection methods.

One promising avenue of research is the analysis of evaporation residuals. The way that liquid droplets dry can contain information about the composition of the fluid and the solute transport [1],[2],[7]. In the case of milk, the morphology of the dried droplet is particularly sensitive to adulterant additions, as these additions affect crystallization and behavior during capillary flow and the deposition of material from the droplet [3], [8], [9].

As a result of advances in machine learning (particularly in the development of convolutional neural networks), researchers now can automate the analysis of complex visual features, such as textures, cracks, and crystalline structures, which have previously only been possible to obtain by manual inspection using a microscope [10]–[12]. Numerous studies have shown that combining residue pattern imaging with deep learning improves food quality assessment and detects adulterated foods [11], [13], [14].

In this study we present our new integrated system, integrating controlled droplet evaporation of milk, image analysis using a microscope, and classification using CNN technology as a means for determining if the milk has been adulterated. The system will provide low-cost, scalable alternatives to traditional laboratory testing while producing accurate classification results.

II. OBJECTIVE:

This study has five goals: The first goal is to create a carefully controlled set of real and fake (adulterated) milk samples using freshly collected samples of milk from One of the Milk Center Akurdi containing targeted types of adulterants at known levels. Second, generate evaporation residue patterns by depositing fixed volumes of droplets of milk on glass slides and letting them dry under controlled conditions. Third, obtain a structured, known reference dataset of microscopy images of each droplet (one each of complete, three edges, and three centers) at constant illumination and magnification. Fourth, organize the microscopy images obtained into a labeled database of images for both type and level of milk adulteration. And fifth, develop and present a CNN-based classification methodology for determining whether there has been an adulteration based on the morphology of the residue, without the use of a non-CNN classifier.

III. LITERATURE REVIEW:

The physical principles behind residue-pattern analysis come from studies of droplet evaporation. In their research, Deegan and colleagues demonstrated that ring-shaped deposits are formed by etched droplets that create capillary flow outward from their rim due to evaporation occurring at the droplets' edge [1]. This mechanism provides the basis for understanding the radial deposit patterns formed by droplets of colloidal and biofluid materials. Subsequent reviews have indicated that the dried morphology of droplet deposits is influenced significantly by fluid composition and how it interacts with the substrate material, the external environment (e.g., temperature, humidity), as well as the manner in which the fluids move to their final resting place on their respective surfaces; therefore, imaging these deposits can be used as a method to characterize residue on surfaces [2].

In addition to this, many researchers studying milk adulteration have utilized evaporation-based techniques to identify products that can be adulterated. Kumar and Dash reported a low-cost method that uses heated air to identify the addition of water or urea to milk based on the morphology of the final deposit formed [3]. Similarly, Harindran et al. researched how dried milk droplets from distinct processes would form different manifest shapes and that these shapes could contain enough unique characteristics to allow for the creation of an automated classification system [4]. Finally, Ishwarya and colleagues applied the sessile-bloating technique in studying milk to detect added starch and established that the morphologies of deposits will vary based on the concentration of starchy material [5].

Image analysis has also been useful in determining how to identify different types of substances in dried residue. Carreón et al. found that the characteristics of droplet deposits could be identified using texture-derived image descriptors, and they emphasized the need for the use of image analysis to capture structured visual characteristics, including crystallite organization, surface irregularity or roughness, and localized relationships of intensity [6]. This work demonstrates that differences in edge buildup of residue, center build up, and crystal morphology of milk residues are affected by the chemistry of their adulterants.

Additional work has used residue imaging from evaporative milk deposits in a dataset applied to a CNN (convolution neural network) to classify residue and determine differences in residue patterns caused by different adulterants, as shown by Mamgain et al. [7]. The use of residue pattern imaging (such as the coffee-ring effect) with the CNN by Persian et al. has provided further evidence of the potential of combining residue morphology and deep learning to address consumable product inspections for adulteration [8].

The research presented here expands on these studies, but does so in a different experimental context (milk from a specific local source, in addition to a defined microscopy procedure, and a concentration-dependent classification of milk for water, sugar, salt, and detergent). As such, the existing literature provides two important underpinnings for the current research: residue morphology is dependent on residue composition, and CNNs can learn the differences in composition from images of residue [1]-[8].

Advances in new tools leveraging sensing and machine learning to detect milk adulterants have been published in recent investigations [15]-[17]. Specifically, researchers have found that combining spectroscopic and hyperspectral imaging methods with machine learning models achieves a very high detection accuracy rate for identifying a wide variety of adulterants. Furthermore, real-time and portable methods of detecting adulterants have been developed through the use of edge-based AI implementations and sensor-based detection methods [18]-[19]. These publications illustrate a clear trend towards using a combination of imaging & sensing technologies with deep learning approaches to provide a comprehensive assessment of the quality of food products.

IV.METHODOLOGY:

A. Sample Collection and Adulteration Protocol

Fresh cattle's milk samples were taken from a local milk supply center located in Akurdi. The fresh milk samples were treated as pure milk references (i.e. no contaminants) and no other means of production /adulterants. Controlled adulteration of the pure fresh milk was accomplished using four common food additives (water, sugar, salt, and detergent) [3],[4]. Pure milk was adulterated by adding 10, 20, and 30%

of water to the milk sample, with the added sugar, salt, and detergent being from 1 to 5 grams. As a result, there are therefore five classes created (1 pure and 4 classes each holding 1 type of adulterant), which facilitate the classification of the samples.

B. Droplet Deposition and Evaporation

5-10 μL of each milk sample was dropped on standard glass microscope slides and allowed to evaporate under controlled conditions for temperature, humidity, and airflow. Since these factors impact evaporation rates and morphology of milk residue [1],[2] it was critical to provide a constant temperature, humidity, and airflow environment during the entire evaporation period.

Dried residue left behind after the evaporation of milk serves as a physical signature for characterizing the content of milk. All quantities of dissolved particles (solutes) in the liquid milk and added contaminants will result in a different flow of internal liquid; will cause crystals to develop at different rates; and will cause different deposition patterns of the dried residue left from the evaporating milk. Such deviations in the physical characteristics of the dried milk residue can be used to determine the authenticity of the milk from which it was obtained [2],[3],[5].

C. Microscopic Image Acquisition

After all the droplets have evaporated, images of the droplets were captured using a microscope by using the following imaging protocols for each droplet: one full image (captures the complete residue global geometry including overall ring shape, radial nonuniformity, and macro cracks), three images of the edges of the droplets (captures contact line deposits, ring compaction, accumulation of crystals, and boundary roughness), three images of the center of the droplet (captures texture of the internal deposits, crystallite arrangement, and any discontinuities/voids formed during the last stages of drying).

D. Dataset Construction and Labeling

The labels used to determine the type of adulterant, concentration, and droplet location (whether edge, center, or entire droplet) were attached to each image so that evaluation of the datasets could be consistent. This was done at the level of the droplet and NOT the image to ensure that droplet images were not being used across all sets.

The dataset includes multiple droplets from each class, with 7 images created by each droplet (one full view, three edge views, and three center views). In total, around 7 droplets were collected for each class, producing 49 images for each class. The dataset was partitioned into training (70%), validation (15%), and testing sets (15%) at the droplet level to prevent data leakage by ensuring all images from a single droplet are within the same partition.

E. Image Preprocessing Pipeline

The preprocessing phase for residue images involves uniformity of images, as well as highlighting areas of interest on residue images to aid in the training of the CNN. The first step is uniformly scaling all the images to a specific size and normalizing them. This helps keep all the images consistent with each other. Keeping the original RGB format of the image maintains the discrepancy of residue textures and color variance.

Finally, data augmentation techniques such as degree of rotation, flipping, zoom, and contrast are used to aid with generalizing the model by helping to decrease the overfitting of training samples. Preprocessing images through these methods assists the CNN to rely on physical properties such as ring thickness, crack distribution, and crystal patterns when generating a training sample.

F. CNN-Based Classification Pipeline

The CNN model processed preprocessed images, with each image being an RGB-normalized residue image to a multi-class classification model. The convolutional and pooling stages of the CNN create hierarchical representations of features within each image.

The final layer determined which labeled class is assigned to the residue image, and is based on its classification (either as pure milk or as an identified set of adulterant-concentration combinations).

Reports were generated at the imager level (from the CNN) and also provide aggregated results at the droplet level for three views of the droplet - full, edge, and center - when desired. Multi-view results can add value because both edge and center regions have distinct physical characteristics of the normal drying process.

In order to facilitate reproducibility and minimize data leakage, all partitions of the dataset have been strictly performed at the droplet-level as opposed to the image-level; i.e., each droplet produces multiple images. This consideration has also been emphasized for other food analysis research utilizing machine learning methods [11] ,[16]. Additionally, all variables potentially influencing residual patterns were held constant by developing controlled conditions (e.g., temperature & humidity) and maintaining similar levels of illumination [2], [7].

G. Implementation Details

The proposed CNN model was developed with a deep learning framework such as TensorFlow/Keras. Training was done using the Adam optimization algorithm combined with categorical cross-entropy as the loss function. The training set, validation set, and test set were divided using a droplet-level split in order to avoid data leakage. In addition, early stopping and learning rate scheduling were utilized in order to maximize convergence and to reduce potential overfitting.

V. CNN ALGORITHM EXPLANATION:

The system proposed in this study uses a convolutional neural network (CNN) to identify microscopic images of evaporation residue of milk as pure or mixed with other materials. Since CNNs automatically learn visual features from the data they use, they are able to do a good job of classifying these types of images based upon many different hierarchical features, including edges, textures, cracks, ring boundaries, and patterns of crystals.

In this instance, the CNN is provided with pre-processed evaporation residue images during training for each of the different types of adulterants (and concentrations) that would require classification; therefore, the CNN learned patterns associated with each category to enable it to accurately classify the images.

A. Convolution

In the convolution layer, a filter kernel is slid over the input image to extract local spatial features. For an input image X, filter W, and bias b, the feature map $F$is expressed as

$$F = f(X * W + b)$$

where $*$denotes convolution and $f(\cdot)$is the activation function, typically ReLU. The ReLU function is defined as

$$f(z) = \max(0, z)$$

This stage captures local structures such as residue edges, radial streaks, crack-like regions, and crystallization patterns.

B. Pooling

Pooling layers reduce the spatial size of feature maps while preserving the most important information. For max pooling over a region Ω, the output is

$$P = \max_{x \in \Omega} F(x)$$

Pooling reduces computation, limits overfitting, and improves robustness to small positional changes in the residue images.

C. Classification

After several convolution and pooling stages, the extracted features are flattened and passed to fully connected layers. The final output layer uses SoftMax to produce class probabilities. For class i, SoftMax is defined as

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where $z_i$is the score for class $i$and $C$is the total number of classes. The predicted label is the class with the highest probability.

D. Loss Function and Training

The network is trained using categorical cross-entropy loss:

$$L = -\sum_{i=1}^{C} y_i \log(p_i)$$

where $y_i$is the true label and $p_i$is the predicted probability. The parameters are optimized using backpropagation with the Adam optimizer. To improve generalization, data augmentation such as rotation, flipping, zooming, and contrast variation is applied during training.

E. Summary of the CNN Pipeline

As a result, CNN learns a series of features based upon the types of residues associated with the adulterants in a hierarchical fashion (i.e., the CNN uses convolution to extract local patterns, uses pooling to reduce dimensionality, and finally assigns the image to the class of the correct milk type/image via a SoftMax function). The end result is that through the use of microscopic images of evaporation residues, the proposed system was able to provide accurate classification of pure milk and of adulterated milk samples.

VI. RESULTS:

A. *Representative Residue Morphology*

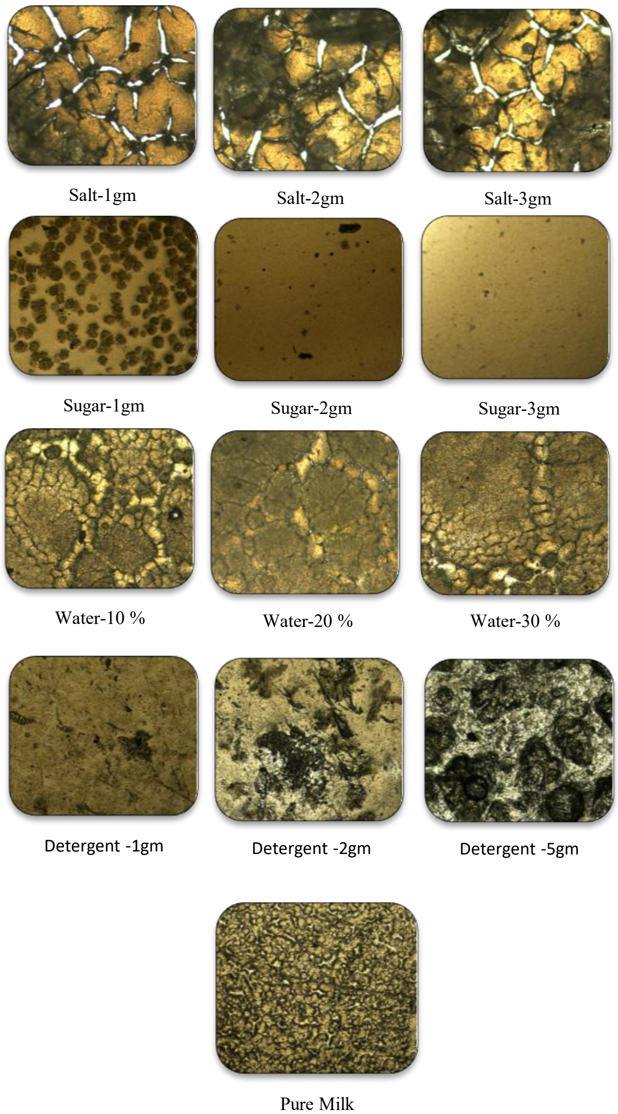

Fig. 1. Representative microscopic residue patterns for pure milk and adulterated milk samples.

B. *CNN Classification Outcome*

From the confusion matrix in Fig. 2, it is shown that the CNN model achieves high classifications almost all classes. This is especially true for the class of detergent, pure milk, and salt samples, all of which were classified perfectly at 100% accuracy. Water samples had a high level of misclassifications at one, and there was slight confusion in the classification of sugar over pure milk.

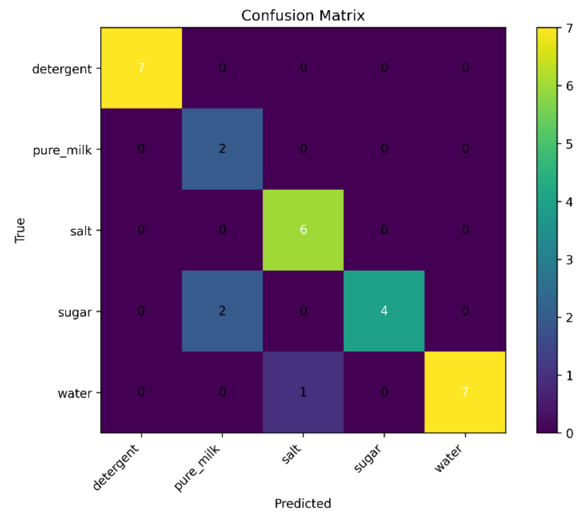

Fig. 2. Class-wise confusion matrix for CNN predictions on the test set.

C. *Quantitative Performance Summary*

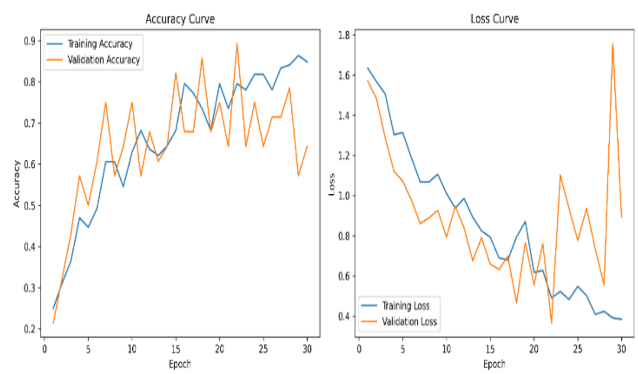

Fig. 3. Training and validation accuracy and loss curves of the CNN model.

The overall classification accuracy of the proposed model is approximately 89.6%. Class-wise performance indicates that detergent, salt, and pure milk achieved perfect classification. Sugar samples were classified with an accuracy of approximately 66%, while water achieved approximately 87.5% accuracy. The results confirm that the CNN effectively captures discriminative residue features.

The accuracy curve indicates a steady increase in training accuracy, reaching approximately 85%, while validation accuracy fluctuates between 60% and 90%. The loss curve shows a decreasing trend for training loss, whereas validation loss exhibits slight fluctuations due to limited dataset size. These results indicate that the model effectively learns discriminative features while maintaining reasonable generalization performance.

VII. Conclusion:

The research presented in this article provides a full framework to quantitatively assess milk quality by using both evaporation residue patterns and convolutional neural networks (CNNs) to classify if there is an adulterant present in milk. The framework incorporates controlled experimental conditions, microscopic imaging of the residue patterns, and the application of deep learning to classify whether there is an adulterant in the milk or not. Results from the study concluded that morphological features of the evaporation residue patterns could provide reliable indicators of the composition of the milk, and the CNN models could learn recognizable discriminatory features. The initial efforts of the proposed framework were successful at achieving the overall classification accuracy level of approximately 89%. However, future work will focus on increasing classification separability, enlarging dataset sizes, and improving the robustness of the classification in different environmental conditions. This method provides a cost-effective alternative to evaluate the quality of the milk at any given time, producing an efficient, rapid assessment framework that may be utilized for food safety monitoring systems.

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