A Novel Approach for Honey Adulteration Detection Using Thermal Imaging and Convolutional Neural Networks

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Abstract

For life to be sustained and nourished, food is necessary. Food composition and quality are impacted when adulterants are added. Adding sugar syrups to honey in order to increase its quantity and lower its price is one of the most prevalent forms of food adulteration in honey. Health issues as well as other negative consequences may result from this. This technology will ensure that customers have access to safe and nutritious food by offering a dependable and reasonably priced solution for the detection of honey adulteration. Additionally, it will lessen the detrimental effects on the environment and economy by preventing the selling of tainted honey. The non-invasive, non-ionizing, complementary diagnostic and real-time monitoring method known as thermal imaging makes it possible to see and measure variations in the temperature of honey. The honey's temperature changes can be detected by a thermal camera. With the use of a Convolutional Neural Network (CNN) algorithm, we present a novel method for identifying honey adulteration. The proposed system consists of two main stages: Preprocessing and Classification. The honey sample's input picture is treated during the preprocessing phase to improve its characteristics and eliminate noise. During the classification phase, the CNN algorithm receives the processed image and determines if it is contaminated or not. The suggested approach can be used in food quality control systems because it is quick and requires little human involvement. This approach can protect consumers' health and well-being by assisting in ensuring the safety and quality of food products.

***Keywords**: Adulteration, Deep learning, Thermal Images, Convolutional Neural Network (CNN), Honey.*

INTRODUCTION

A natural, nutrient-rich substance made from floral nectar, honey is prized globally for its culinary applications, therapeutic qualities, and health advantages. Bees process it. It is an unusual and highly sought-after food product because it contains a complex mixture of carbohydrates, enzymes, vitamins, minerals, and antioxidants. However, adulteration has become common due to the rising demand for honey and its comparatively high market value. Concern over honey adulteration is rising among farmers, consumers, and regulators, among other stakeholders. It calls into doubt both the genuine medical benefits of honey and the safety of food for consumers. Financial losses and unfair competition are the results of adulteration for legitimate honey producers. Analyzing current detection technologies and comprehending the elements that contribute to this unethical activity are essential. Honey can be adulterated in a number of ways, including directly by adding sugars like glucose, fructose, and sucrose, as well as by the addition of corn syrup and rice syrup. It is also possible to add water to boost volume. There are several methods used to detect honey adulteration.

Here are Some Common Types:

Physical Method: - Water Solubility Test: Pure honey takes a long time to dissolve in water. Honey may be contaminated if it dissolves right away. As time passes, real honey has a tendency to crystallize. If it stays liquid for an extended length of time, it can indicate adulteration.

Hydroxymethylfurfural (HMF) Test: As honey matures, a chemical called HMF is formed. HMF levels that are too high may be a sign of adulteration or heat treatment. Conductivity Test: The range of conductivity of pure honey is particular. Increased conductivity may suggest the presence of syrups or added sugars.

Methods of Spectroscopy: By comparing spectral fingerprints, infrared spectroscopy may detect adulterants and assist in analyzing the chemical makeup of honey.

Nuclear Magnetic Resonance (NMR): NMR may identify adulteration and offer comprehensive details on the chemical makeup of honey. Methods of Chromatography: Honey's sugars and other constituents may be separated and quantified using High-Performance Liquid Chromatography (HPLC), which also helps detect any adulteration. Gas Chromatography-Mass Spectrometry (GC-MS): This technique can identify tampered honey by identifying harmful chemicals and volatile components.

Sugar Addition: This technique identifies sugar additions that are higher than 7% (up to 10%). It cannot be adulterated with beet syrup since the enzymes break down the additional sucrose to less than 5%. However, the feeding of colonies with C3 sugars, such as those found in rice, wheat, and beets, cannot be detected by isotope analysis.

Adulteration with Specific Sugars: It determines the amount of glucose, fructose, sucrose, and maltose in honey using chemometrics and Fourier Transform Infrared Spectroscopy (FTIS). Using commercial honey samples and high-performance liquid chromatography, the model was validated. The study demonstrated that honey adulteration can be detected using the FTIR approach. At 7%, 14%, and 21%, each mixture was applied to a honey sample. The K nearest neighbors (KNN) and partial least squares (PLS) regression approaches were used to compress and evaluate the spectral data. A PLS regression with an overall classification rate of 93% produced the best classification. 99 % of the samples that were tainted at 14% or more were accurately recognized by this model. This approach is a quick screening procedure to find this kind of adulteration.

These methods can vary in complexity, cost, and equipment requirements, so the choice of method often depends on the level of accuracy needed and available resources.

RELATED WORKS

Due to the globalization of trade and the growing consumer demand for safe and high-quality food and agricultural goods, many nations are paying particular attention to stricter standards for food safety and quality. This technique is used to identify heat sources by detecting infrared radiation. It then converts these laser signals into electrical impulses.

Traditional grading techniques are still widely used today, although the post-harvesting business started using automation in classification processes due to their high cost and certain irregularities. Automated grading systems reduce the inconsistencies that come with manual grading, which lowers the error rate and expense, but they also accelerate rises. Designing an automated system with developed conveyer platforms reduces the laborious human inspection work of sorting veggies. In order to reduce post harvest losses, this research proposes an effective non-destructive Infrared Thermal Image Processing Technique for Vegetable Quality Detection and Separation. To avoid post-harvest losses, the study suggests separating and detecting vegetable quality using an effective, non-destructive infrared thermal image processing method. In addition to lowering expenses and speeding up the grading process, automated grading systems that employ this method can lessen the faults and inconsistencies that come with manual grading. The laborious process of manually inspecting and sorting veggies can be lessened with the automated system that has conveyor platforms.

[3] Using machine learning techniques such artificial neural networks (ANN), support vector machines (SVM), K nearest neighbors, random forests, and decision trees, this study attempts to create a honey counterfeit detection system that is both accurate and efficient. The suggested model solves generalization to unidentified honey types of problems by relying on hyper-spectrum imagery. Hyperspectral pictures of adulterated honey samples from seven distinct brands with twelve different botanical origin labels that have been segmented and pre processed are included in the dataset. Honey's botanical sources are categorized using feature reduction approaches, including feature ranking-based feature selection and autoencoder algorithms. Algorithms including ANN, SVM, KNN, random forests, and decision trees were employed by the researchers.

[4] In this paper, there are various kinds of machine learning algorithms, depending on how they are used in the adulteration detection industry. Although there are several technologies for classifying honey, the most of them are damaging and excessively expensive in terms of time, money, and personnel.

[11] In this case, destruction refers to the honey samples being harmed or compromised by traditional technologies. By contrasting the widely used methods, this study aims to enhance the machine learning-based detection of honey adulteration. The following is a discussion of the review of related research works in this area.

[12] Convolutional neural networks (CNNs), a machine learning algorithm, were used in the recent work described in this research to suggest an effective and non destructive method for identifying fruit freshness. Conventional techniques including manual labour, testing reagents, and instruments take a lot of time and effort. A high-value food, fruit can rot while being packaged, transported, and sold. Based on experimental results, the paper examines overfitting of machine learning and demonstrates that CNNs perform well in determining the freshness of fruit.

[19] The main contributions of this paper are the introduction of a new feature smoothing technique to conform to the classification model used to detect the adulterated samples and the perpetration of an adulterated honey data set using hyperspectral imaging, which has been made available online for the first time. 95% accuracy was achieved for

binary adulteration detection and multi-class classification between different adulterant concentrations. This paper develops a new approach to fraud detection in honey, specifically examining adulterating honey with sugar and using hyperspectral imaging and machine learning techniques to detect adulteration.

PROBLEM STATEMENT

Hyperspectral imaging was used to detect adulteration between sugar syrup and honey using a neural network with 95 % accuracy in. The approach used was different to our method, as they did not use segmentation on the hyperspectral images. Instead, they used an entire hyperspectral image as a single training/testing example. The accuracy achieved is lower than our accuracy. Additionally, honey that has been tampered with cannot contain the elements that are vital for a healthy body. Thus, it is critical to identify this type of adulteration in order to guarantee the food's safety and quality. Though the results are neither precise or trustworthy, human perception based on visual inspection has long been acknowledged as a guide for evaluating quality. This work addresses these problems by proposing a Convolutional Neural Network (CNN) method detect counterfeiting in honey, and using the thermal imaging concept for the collection of datasets. Thermal imaging is used to observe the internal temperature radiation of an object. The proposed work achieves an accuracy of over 97%

PROPOSED SYSTEM

Thermal images of pure honey, adulterated honey with sugar syrups, glucose syrup, are captured and it serves as a dataset for developing, evaluating, and verifying the model. The strategies employed and the image processing algorithm implemented are briefly detailed below. The digital images of pure honey, adulterated honey with sugar syrup, glucose syrup is shown in fig.1. There are serious health dangers associated with fake honey, which is sometimes tainted with chemical sweeteners and sugar syrup. These include reduced immunity, possible organ damage, weight gain, and digestive issues. Honey that has been adulterated can have a number of detrimental health effects. It can boost blood lipid levels, elevate blood pressure, and raise blood sugar levels, every one of which can lead to diabetes, obesity, and weight accumulation around the abdomen. According to multiple in live study designs, the liver is the organ that is most frequently impacted by honey adulterants, followed by the kidney, heart, and brain. Consuming contaminated food is extremely harmful and can result in a number of medical problems, such as kidney problems, some diseases caused by a lack of nutrients, and failure of the heart, kidney, and liver.

Concept of Thermal Imaging

Thermal imaging technology, also known as infrared thermography, uses infrared radiation to capture and examine temperature changes in objects and scenes. It is impossible to perceive infrared radiation directly with the human eye. Infrared radiation, whose intensity is directly related to an object's temperature, is theoretically emitted by all objects. Warmer objects release more infrared radiation than cooler ones. Consequently, a wide range of industries are using infrared thermal imaging. It can be applied in any situation where temperature variations are required to facilitate the identification, evaluation, or analysis of the item or activity By integrating thermal imaging systems with other technologies, such as artificial intelligence and machine learning, their autonomous object recognition and anomaly detection capabilities have been enhanced. A crucial and adaptable technology, thermal imaging is always evolving and finding new uses in a wide range of industries. The thermal images of pure honey, adulterated honey with sugar syrup is shown in fig 1.

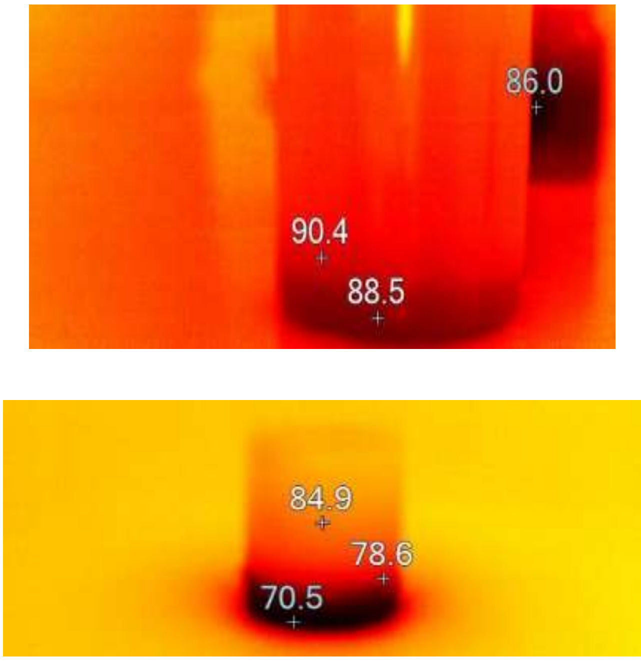

Figure 1 Thermal Images of Pure Honey and Adulterated Honey

A thermal camera, also known as an infrared camera or a thermographic camera, is a device that creates images of surfaces and objects within its field of view based on temperature variations between them using infrared light. Thermal cameras capture heat emissions from objects and convert them into visible images, as opposed to visible light cameras, which capture the light that is visible to the human eye. The basic idea behind a thermal camera is to detect infrared radiation that objects release. The camera's sensor absorbs this radiation, creating an image where each pixel represents a distinct temperature. Thermal cameras can measure and display temperature variations in real time.

Characteristics of Thermal images: Infrared radiation is a type of electromagnetic radiation that is longer than visible light (400 to 750 nm) but shorter than microwaves (above 1 mm) in the electromagnetic spectrum. Infrared radiation typically has wavelengths between approximately 750 nm and 1 mm. Because of their longer wavelengths than visible light, infrared waves can pass through dense regions of gas and dust in space without being significantly scattered or absorbed, and because human eyes are only sensitive to the visible light spectrum, infrared radiation cannot be seen by humans. Infrared waves are classified as transverse waves and have characteristics such as absorption, reflection, refraction, and interference. The absorptivity, emissivity, transmissivity, and reflectivity vary depending on objects and materials.

The temperature of a body that absorbs all radiation that strikes its surface is how the Stephan-Boltzmann Law characterizes the power radiated by that body. The following formula can be used to express the radiation energy emitted by a black body per unit time, which is proportional to the absolute temperature to the fourth power. Power radiated is defined by,

$P = \epsilon \sigma T4 A$ Watts

Where P: Radiation energy/power

σ: Stefan-Boltzmann Constant

T: Absolute temperature in Kelvin

ϵ: Emissivity of the material

A: Area of the emitting body

When using a thermal camera, infrared detectors measure radiation coming from an object's surface in the spectral range of 35 m (short wave) or 8–12 m (long wave).

Hardware Setup

Figure 2 Thermal Camera Setup

The thermal camera configuration is shown in fig. 2 above. Thermal cameras come in a variety of models, such as handheld cameras, professional and universal cameras, industrial thermal cameras, and infrared radiometric thermal cameras. The two most crucial factors to take into account when buying a thermal camera are thermal sensitivity and detector resolution.

The system's hardware consists of the Thermal Image Capturer, the MSI RAIDER GE77 laptop, and the insulated chamber that holds the food items that need to be verified. Here is a basic description of the setup. After receiving the photos from the camera, the laptop processes them for additional categorization and examination. All that is needed to complete the process is a basic understanding of how to use a thermal imaging camera. The camera is aimed at the insulated chamber, as shown in fig. 3 below.

Figure 3 Insulated Chamber with Camera

The steps for capturing thermal images are as follows:

A small aperture on top of a wooden insulation chamber with the following measurements: 30 cm x 30 cm x 25 cm is built for the thermal camera. The box is properly insulated to prevent heat transfer between the chamber and its surroundings.

The honey is positioned within the chamber in the desired areas, and the picture is then taken.

To identify the presence of adulterants in food products, the collected images are subsequently supplied to the CNN model.

The technology alerts the user if the honey contains an adulterant. The insulation chamber is made of wood, which is a good insulator and keeps environmental heat radiation from affecting the image. Its measurements are as follows: 25 cm in height, 30 cm in width, and 30 cm in length. The interior layer is further cushioned with polystyrene (thermocol) to keep heat from the chamber from escaping into the surrounding air. The surface is then covered with a layer of black paint, which creates a clean background that makes it possible to examine the captured image in its best quality. This layer of black paint effectively absorbs heat, resulting in even quality photos. The fig.4 mentioned above shows the inner and outer structure of the insulation chamber.

Figure 4 Structure of Insulation Chamber

Thermal cameras are versatile technological instruments that improve safety and productivity. Thermal imaging cameras create thermal images using infrared energy. The camera's lens directs the infrared energy onto a collection of detectors, which subsequently generate a complex thermogram pattern. The thermogram is then converted into electrical impulses to create a visible and intelligible thermal image. Warmer items appear yellow-orange on a traditional thermal camera, becoming brighter as you approach them, while colder objects take on a blue or purple hue. The thermography apparatus is based on a portable camera with an image processing system (usually supplied by the vendor) that can capture both RGB and thermal images. When compared to hyperspectral imaging, its advantages include the equipment's low cost and simplicity of use, as well as the absence of the necessity for fiber optics or a diode array detector during operation. Thermal imaging cameras typically capture images with a pixel size of 320 × 240 to 1280 x 960 pixels, with a far-infrared spectral range of 7.5 µm to 13 µm, and deliver highly accurate temperature readings (up to 1200 °C). The Fluke Thermal Camera, model TiX580, is a high-performance thermal imaging camera manufactured by Fluke Corporation that was utilized in this project. The TiX580 is renowned for producing crisp, detailed thermal images due to its exceptional thermal resolution. For many applications, the thermal resolution—typically 640 × 480 pixels—is regarded as excellent. It has a 240° tiltable touchscreen and a temperature range of up to 1832°F (1000°C). The TiX580's touchscreen interface may be easy to use, making it quick and easy to browse menus, adjust settings, and see thermal images on the camera's screen. It probably has a number of connectivity features, such Bluetooth or Wi-Fi, which let you move data and photos to a computer or mobile device for reporting and analysis. The camera may have built-in temperature analysis tools, including temperature profiles, spot temperature monitoring, and more. It can be used for a variety of purposes and has a long battery life. The Fluke Thermal Camera TiX580 is depicted in fig. 5 below.

Figure 5 Fluke Thermal Camera TiX580

Software Setup

The software elements of this work include SmartView® Software and PYTHON libraries to create the CNN algorithm. A huge dataset can be created from a limited number of images by viewing, analyzing, and editing the images using the SmartView® Software. For the Neural Network to be analyzed, this dataset is then split into training, testing, and validation data. Users of SmartView can produce interactive reports, connect to numerous data sources, and carry out data analysis and visualization tasks. The below fig.6 shows the page of SmartView Software.

Figure 6 Smartview Software

Concept of CNN Algorithm

The goal of the machine learning and artificial intelligence (AI) field of deep learning is to make it possible for artificial neural networks to do tasks that typically require human-like intelligence. Deep learning techniques have gained a lot of traction and led to innovative breakthroughs in a variety of domains, such as computer vision, natural language processing, speech recognition, and reinforcement learning. Figure 7 illustrates the fundamental processes of the deep learning technique.

Figure 7 Basic Process of Deep Learning Model

Specialized neural networks designed for computer vision tasks are known as CNNs. Convolutional, pooling, and fully linked layers comprise their composition. CNNs have shown great success in applications like as object detection, picture segmentation, and image classification. It is a special type of deep neural network designed mainly for visual data processing and analysis, including images and videos. They carry out tasks where the spatial relationships between data pieces are essential and are model after the human visual system. The CNN architectural layer is shown in fig.8 below.

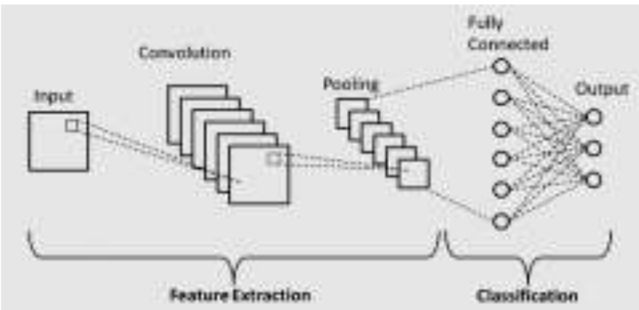

Figure 8 CNN Architecture

Convolutional Layers: Learnable filters (also known as kernels) are used by CNNs to scan the input data using convolutional layers. These filters move through the input, multiplying each element separately, then adding the results to create feature maps. Local patterns and features found in the input data are captured by convolutional layers. The fig.9 mentioned below indicates that the convolution operation has been implemented on a 5 X 5 input and a 3 X 3 filter.

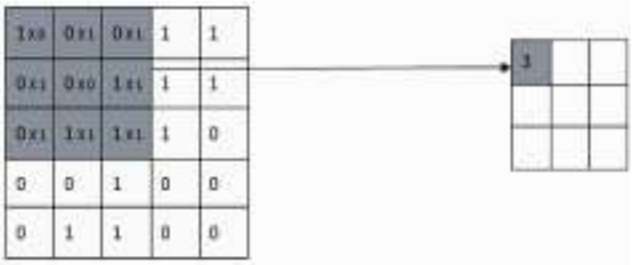

Figure 9 Process of Convolutional Layer

Pooling Layers: Pooling layers, such as max-pooling or average-pooling, are used to shrink the feature maps' spatial dimensions while preserving crucial data. By pooling, the network becomes more resistant to changes in the input. The below fig.10 shows how max pooling is performed in CNN technique.

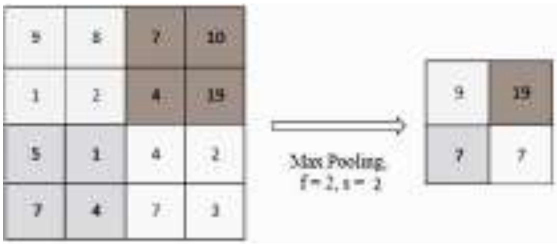

Figure 10 Steps of Pooling layer

Activation function: After convolution and pooling layers, non-linear activation functions like ReLU (Rectified Linear Unit) are used for the feature maps. These give the model non-linearity, allowing it to pick up complicated patterns. Fully Connected Layers (FCLs): Following a number of convolutional and pooling layers, CNNs frequently include one or more FCLs. For final classification or regression, these layers flatten the output of earlier layers and feed it into a conventional feedforward neural network.

Dropout: A regularization method used in CNNs to avoid overfitting is called dropout. During training, it randomly sets a portion of the neurons' outputs to 0, which enhances generalization.

Batch normalization is another method for accelerating training and enhancing the stability of CNNs. Each layer's activations are normalized to have a zero mean and a unit variance.

Strides: To regulate how much the filter moves when scanning the input, convolutional layers might employ strides. Smaller feature maps are produced by a higher stride value.

Padding: Before convolution, padding can be applied to the input to regulate the feature maps' spatial dimensions. "Same" padding keeps the spatial dimensions, while "valid" padding means no padding is added, resulting in smaller feature maps.

Typically, CNNs are built in a hierarchical fashion, with a number of convolutional and pooling layers, to extract progressively complex, and sophisticated characteristics from the input data. Based on the specific work and dataset, the network's architecture may change.

CNN Approach

Algorithm

Detecting food adulteration in honey is a challenging task due to the complex nature of the adulterants used. However, one of the most effective ways to detect food adulteration is by using machine learning algorithms such as Convolutional Neural Networks (CNN). A CNN is a deep learning algorithm that is commonly used for image classification tasks. The algorithm works by identifying patterns in the input images and then using these patterns to make predictions about the contents of the thermal image.

To use CNN for detecting food adulteration in honey, the following steps are usually taken:

Dataset Collection

Capture thermal images of pure honey and adulterated honey samples. Use thermal camera to record the temperature distribution of honey at specific conditions.

Preprocessing

- Normalize thermal images to a standard size and scale.
- Perform data agumentation (rotation, flips, brightness adjustments) to improve model generalization.

Model Design

Use a CNN architecture with layers to design a model.

Training

Divide the dataset into training validation and test sets (e.g.,70:20:10).

Evaluation

Evaluate the model using adulteration or non-adulteration.

Flow Diagram

Figure 11 Represents the Flow Diagram of CNN

INPUT DATA CNN ARCHITECTURE (TRAINED MODEL)

IMPURE HONEY

PURE HONEY ADULTERATED HONEY

Figure 11 Flow Diagram of CNN

Data Collection: Collect a large dataset of images of different types of honey, including both pure and adulterated samples. For adulteration, the dataset should also include images of sugar syrup that is commonly used to adulterate.

Preprocessing: Preprocess the dataset to normalize the images, resize them, and convert them to grayscale if necessary.

Training: Train a CNN algorithm on the preprocessed dataset. The CNN model should have multiple convolutional and pooling layers to extract features from the input images. The output layer should have two neurons for binary classification - one for pure honey and the other for adulterated honey.

Testing: After training, test the CNN model on a separate validation dataset to evaluate its accuracy and performance.

Deployment: Finally, deploy the model to detect adulteration in real-time. To do this, capture an image of the honey sample and pass it through the CNN algorithm. The output will indicate whether the honey is pure or adulterated with sugar syrup.

Overall, this proposed system can effectively detect food adulteration of honey with sugar syrup using a CNN algorithm. However, it is important to ensure that the dataset used for training and testing is diverse and representative of different types of honey and contaminants.

Additionally, the model may need to be updated over time as new forms of adulteration emerge.

The working of a CNN can be explained as follows: The input image is passed through the input layer, and the convolutional layer applies a set of filters to the image to extract features. The ReLU layer applies a non-linear activation function to the output of the convolutional layer, introducing non-linearity into the model.

The pooling layer downsamples the feature maps to reduce the spatial dimensionality of the output.The fully connected layer takes the output of the previous layers and flattens it into a 1D vector. The output layer produces the classification output based on the input image. During the training phase, the CNN learns the weights of the filters in the convolutional layer and the weights of the neurons in the fully connected layer through backpropagation. Backpropagation is an optimization algorithm that adjusts the weights of the model based on the difference between the predicted output and the actual output. Once the CNN is trained, it can be used to classify new input images by passing them through the trained model. The output of the model is the predicted class of the input image. In summary, a CNN is a deep learning algorithm used for image recognition and classification. It consists of several layers, including convolutional, ReLU, pooling, fully connected, and output layers. The CNN learns the weights of the model through backpropagation during the training phase, and it can be used to classify new input images during the testing phase.

IMPLEMENTATION OUTCOMES AND REVIEWS TESTING AND EVALUATION

Dataset

When a dataset is examined, it is divided into different phases and the performance of the dataset and classifier is assessed by how well they recognize object. The suggested Convolution Neural Network (CNN) is trained, validated and tested using images (around 500) acquired from a thermal camera classified with two classes. The complete image database has been randomly divided into following groups: 400 images for Training and Validation phases, 100 images for Testing phase.

The below fig.12 and fig.13 shows the results obtained during testing phase of the proposed work. Here the classification of 2 different labels have been achieved perfectly.

Figure 12 Results for Testing Phase

Figure 13 Results for Testing Phase

CONCLUSION

Adulteration of honey with sugar syrup is a common problem in the food industry, and reliable and efficient methods are required to detect such adulteration. The CNN algorithm is a powerful tool for detecting adulteration in honey with a high degree of accuracy. The algorithm takes an image of the honey as input and extracts features from it using convolutional layers. These features are then fed into a fully connected neural network that classifies the image as adulterated or not adulterated based on the extracted features. In a study conducted by researchers, the CNN algorithm was able to classify the images of dal with an accuracy of 98%. The CNN algorithm can be integrated with other technologies like image processing and computer vision to develop automated systems for detecting adulteration in honey. These systems can be used in laboratories to ensure the quality and safety of the honey. CNN can also help reduce the time and cost involved in detecting adulteration in honey, making it an attractive solution for the food industry. The use of the CNN algorithm for detecting adulteration in honey has great potential for improving the quality and safety of food products.

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