Fruit Sorting and Grading Using CNN and Local Binary Patterns (LBP)

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Abstract: **On This project focuses on automating fruit classification and grading using deep learning techniques, particularly leveraging the ResNet (Residual Network) architecture. Traditional methods for classifying and grading fruits are often labor-intensive, time-consuming, and susceptible to human error. As the demand for high-quality, consistent produce increases, the need for efficient and accurate fruit grading systems becomes crucial. The ResNet model, known for its deep architecture and ability to handle complex visual data, is employed to identify and categorize different fruit types based on various characteristics such as color, shape, and texture. By training the network on a large dataset of fruit images, the modelcan not only classify different fruit types but also grade them according to predefined quality standards. This approach significantly reduces human involvement and enhances the consistency and speed of the grading process. The project aims to demonstrate how deep learning can revolutionize agricultural practices, improving market efficiency, reducing waste, and ensuring higher-quality produce for consumers. Furthermore, the proposed solution can be integrated into smart farming systems to provide real-time, automated grading solutions.**

1. INTRODUCTION

The system utilizes a deep convolutional neural network (CNN) trained on a large dataset of fruit images, enabling precise classification and grading. By leveraging ResNet's ability to handle deep networks, the model delivers high accuracy in recognizing complex fruit features. The grading process evaluates ripeness, blemishes, and defects to ensure consistent product quality. This automated solution reduces reliance on manual labor, improving operational efficiency and cutting down on grading errors. As it adapts and learns over time, the system continues to enhance its performance, offering a scalable solution for modern agriculture and smart farming integration.

1.1 OBJECTIVE

The "Multi-Fruit Classification and Grading Using Deep Learning" project aims to automate the classification and grading of fruits in agriculture, enhancing efficiency, accuracy, and consistency. By using deep learning techniques, particularly the ResNet architecture, the system will classify fruits based on attributes like color, shape, size, and texture, and grade them according to quality standards such as ripeness, blemishes, and defects. The project focuses on developing a deep CNN model trained on a diverse fruit image dataset, integrating real-time processing, optimizing performance for large-scale deployment, and ensuring scalability across various fruit types and markets. It will be integrated into smart farming environments, working alongside sorting and packaging machines to streamline workflows, reduce operational costs, and improve product quality. A user-friendly interface will allow farmers and distributors to easily access classification and grading results, monitor system performance, and adjust for improved accuracy. Ultimately, the project seeks to revolutionize fruit processing, offering a cost-effective, reliable solution for consistent, high-quality produce.

1.2 DEEP LEARNING

Deep learning is a subset of machine learning that utilizes artificial neural networks to solve complex tasks by learning from large datasets. Unlike traditional machine learning methods that require manual feature extraction, deep learning automates this process, allowing networks to learn directly from raw data such as images, text, or sound. Through deep neural networks, which consist of multiple layers of interconnected nodes, each layer learns progressively abstract features of the data, with deeper layers identifying complex patterns. These networks are designed to mimic the brain's information processing, using input layers, hidden layers, and an output layer to process and map inputs to outputs. The strength of deep learning lies

in its ability to learn hierarchical representations of data, such as in image recognition, where early layers capture simple features and deeper layers recognize complex objects. Training a deep learning model requires large labeled datasets and powerful computational resources, often accelerated by GPUs. Deep learning excels at handling unstructured data and large-scale datasets, outperforming traditional methods in tasks like image classification, speech recognition, and natural language processing. It has revolutionized industries like healthcare, finance, autonomous driving, and entertainment, with applications such as language translation and advanced gaming systems. Deep learning's ability to process unstructured data without manual feature engineering has made it a critical tool in solving complex, real-world problems with remarkable accuracy and efficiency.

1.3 ADVANTAGES

Automatic Feature Extraction: Unlike traditional machine learningmethods, deep learning automates feature extraction, eliminating the need for manual input from domain experts. This makes it more efficient and scalable.

High Accuracy: Deep learning models can achieve high accuracy,particularly in tasks such as image and speech recognition, due to their ability to learn complex patterns fromlarge datasets.

Ability to Handle Unstructured Data: Deep learning excels in processing unstructured data like images, audio, and text, which is often difficult for traditional machine learning models to handle effectively.

Hierarchical Learning: Deep learning models learn hierarchical representations of data, allowing them to progressively extract more abstract and complex features from raw data. This is especially useful in tasks like image classification and natural language processing.

2. LITERATURE REVIEW

1.The paper titled "Multi-Fruit Classification and Grading Using a Same-Domain Transfer Learning Approach," published in MDPI, Volume 13 (2024), by Lama A. Aldakhil and Aeshah A. Almutairi, presents an advanced system for fruit classification and grading using a same-domain transfer learning approach. The authors utilized EfficientNetV2, a cutting-edge convolutional neural network, and enhanced its performance through extensive data augmentation techniques to improve accuracy and robustness. The system was trained and tested on a diverse multi-fruit dataset, achieving an impressive 99% classification accuracy. This research makes a significant contribution to agricultural automation by providing an efficient, scalable solution for real-time fruit sorting and quality assessment.

2. The paper titled "Highly Efficient Machine Learning Approach for Automatic Disease and Color Classification of Olive Fruits," published in MDPI, Volume 13 (2024), by Nashaat M. Hussain Hassan,A. A. Donkol, M. Mourad Mabrook, and A. M. Mabrouk, presents a machine learning-based system designed for automatic disease detection and color classification in olive fruits. The proposed model utilizes advanced image processing and feature extraction techniques, significantly improving the accuracy of classifying healthy and diseased olives, as well as determining their ripeness stages based on color. This research highlights the practical application of machine learning in agricultural quality control, offering a reliable, efficient, and scalable solution for automated olive fruit sorting and disease management.

3.The paper titled "TL-YOLOv8: A Blueberry Fruit Detection Algorithm Based on Improved YOLOv8 and Transfer Learning," published in MDPI, Volume 10 (2024), presents Rongli Gai, Yong Liu, and Guohui Xu, an advanced blueberry fruit detection algorithm built on the YOLOv8 framework and transfer learning techniques. The model incorporates attention mechanisms and optimized loss functions to enhance detection performance, particularly in complex backgrounds and occlusions. Extensive experiments conducted on a custom blueberry dataset demonstrated that TL-YOLOv8 outperforms baseline methods, achieving higher detection accuracy and faster processing speeds. This research provides a practical solution for efficient fruit harvesting, making significant contributions to precision agriculture and automation.

4.The paper titled "A Review on Automated Detection and Assessment of Fruit Damage Using Machine Learning," published in Elsevier, Volume 16 (2023), by Yonasi Safari, Joyce Nakatumba-Nabende, Rose Nakasi, and Rose Nakibuule, provides a comprehensive review of recent advancements in automated fruit damage detection

using machine learning, focusing on both traditional methods and deep learning models like CNNs. It highlights the critical role of image preprocessing, feature extraction, and dataset quality in achieving high performance. The review also addresses challenges such as fruit type variability, lighting conditions, and damage severity, all of which can impact model generalization. The study emphasizes the potential of AI in enhancing agricultural quality control and suggests future research directions, particularly in real-time and multi-fruit damage detection.

3. EXISTING SYSTEM

Existing systems for fruit classification and grading largely rely on traditional methods such as manual inspection, which are labor-intensive, time-consuming, and prone to human error. In agricultural settings, fruits are often graded manually based on visual inspection, leading to inconsistencies in quality assessment. Human inspectors may miss subtle differences in characteristics such as ripeness, size, texture, and minor defects, resulting in variations in the final quality grade. While traditional automated systems use basic image processing techniques, these methods struggle with real-world complexities like varying lighting, different backgrounds, and natural diversity in fruit shapes and sizes. Additionally, traditional machine learning models such as decision trees, support vector machines (SVMs), and k-nearest neighbors (KNN) can work well with small datasets but fail to generalize with larger, more diverse ones. These models also have higher error rates when distinguishing between fruits with similar appearances, reducing their reliability for automated grading. Deep learning models like Convolutional Neural Networks (CNNs) offer better accuracy by automatically learning features from raw data, eliminating the need for manual feature extraction. However, they face challenges like the need for large annotated datasets, overfitting, and model complexity. Many deep learning systems are not optimized for real-time processing, limiting their practical use in large-scale commercial applications. Furthermore, while deep learning has shown promise in fruit classification, integrating grading tasks such as assessing ripeness or identifying defects into a unified system remains a developing area. Most systems focus on either classification or grading, with few offering both effectively. Therefore, there is a significant need for more robust, integrated solutions that can automate both tasks efficiently and accurately across a wide range of fruit types. Despite progress, existing systems face limitations in scalability, accuracy, real-time processing, and handling diverse datasets. Deep learning has the potential to address these issues, but further advancements in model optimization, data acquisition, and system integration are necessary to fully revolutionize fruit classification and grading in the agricultural industry.

4. PROPOSED SYSTEM

The proposed system for multi-fruit classification and grading is designed to utilize advanced deep learning techniques, particularly the ResNet (Residual Network) architecture, to automate and enhance the accuracy of fruit classification and grading processes. Unlike traditional methods that rely heavily on manual inspection or basic machine learning algorithms, this system employs deep convolutional neural networks (CNNs) to automatically learn and extract complex features from fruit images, thereby eliminating the need for manual feature engineering. This approach significantly improves classification performance, as the model is capable of recognizing subtle differences in fruit attributes such as size, texture, color, and ripeness. ResNet, known for effectively addressing the vanishing gradient problem through its residual connections, enables the construction of deeper networks, which enhances the model's ability to process large and diverse datasets. The system is trained on extensive datasets containing images of various fruit types, including apples, oranges, bananas, and more, and can grade them based on predefined quality metrics such as ripeness level, physical size, and surface texture. To further enhance generalization and robustness, data augmentation techniques including rotation, scaling, and color variation are employed during training, allowing the model to perform accurately under different lighting conditions and background complexities. Designed for real-time processing, the system is well-suited for high-throughput environments such as packaging plants and agricultural sorting facilities, where speed and reliability are crucial. By automating both the classification and grading processes, the system significantly reduces manual labor and inspection

time, while increasing the consistency and objectivity of grading outcomes. Furthermore, the system is highly adaptable and scalable, with the capability to include additional fruit types and grading parameters as required, making it a flexible solution for diverse agricultural applications. Its integrated approach to classification and grading not only improves operational efficiency but also reduces the likelihood of human error and ensures uniform quality standards across batches. The system can also adapt to varying environmental conditions such as changes in lighting, background clutter, and fruit presentation, ensuring stable performance. With the ability to evolve with additional training data and new classification needs, this deep learning-based solution provides a future-ready platform for modern agriculture. Ultimately, the proposed system is positioned to revolutionize the fruit classification and grading workflow by delivering a fast, accurate, scalable, and intelligent alternative to manual inspection, contributing to improved productivity, quality assurance, and market value in the agricultural supply chain.

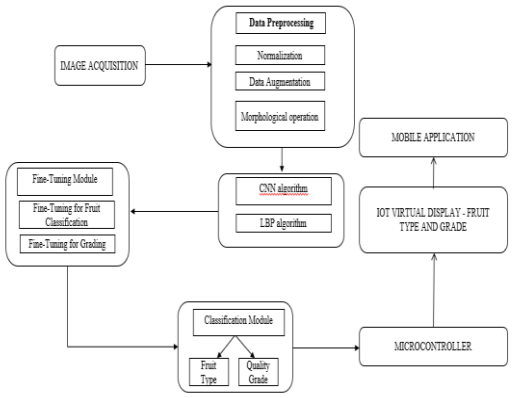

FIG 1. PROPOSED BLOCK DIAGRAM

5. SYSTEM REQUIREMENTS

5.1 Hardware Requirements

The minimum RAM required for the system is 2GB. The processor should be Intel Core i5 or above to ensure optimal performance. A minimum of 2GB of free hard disk space is necessary for software installation and operations. The display should support a screen resolution of 1024 x 768 or higher. In addition to these, hardware components such as the ESP32 microcontroller and a stable power supply unit are essential for interfacing and embedded operations.

5.2 Software Requirements

The system must run on Windows 7 or a later version of the Windows operating system. For simulation and backend services, Python version 3.6 is used along with the Flask web framework. Microsoft Office is used for documentation purposes throughout the development process.

5.3 Software Description

Python is an interpreted, high-level, general-purpose programming language that is widely used across industries. It is especially favored in domains like web development, data science, artificial intelligence, scripting, and automation. Python's clean and readable syntax, dynamic typing, and ease of learning make it suitable for both beginners and professionals.

Python is extensively used in data analysis and machine learning. It is also applied in web development, task automation or scripting, software testing and prototyping, and for handling everyday tasks. Since it has a low barrier to entry, it is commonly adopted by non-programmers such as scientists and accountants for practical applications.

According to Charles R. Severance, the author of “Python for Everybody,” programming is not only a professional activity but also a creative and rewarding one. He emphasizes that Python allows individuals to solve real-world problems, explore data analysis, and develop interesting applications either for fun or for commercial benefits.

Python’s versatility allows it to be used in building web applications on servers, managing workflows, connecting to database systems, and modifying or reading files. It also supports complex mathematical computations, big data processing, fast prototyping, and developing production-ready software solutions.

Professionally, Python is well-suited for backend web development, artificial intelligence, data science, and scientific computing. Developers also use Python to build games, productivity tools, and desktop applications.Python is compatible across various platforms including Windows, MacOS, Linux, and Raspberry Pi. It uses a simple syntax that is comparable to English, which allows developers to write less code than in many other languages. As an interpreted language, it enables immediate execution of code, which is useful during prototyping.

Python supports multiple programming paradigms such as procedural, object-oriented, and functional programming. Its syntax is designed for readability, with structure defined by indentation rather than braces or semicolons. Because Python is dynamically typed, it offers flexibility in coding. It allows the user to test programs up to the point of failure, relying on runtime type checking. This flexibility provides programmers with multiple approaches to solving problems.

However, Python also has some drawbacks. Due to dynamic typing, a single command may have different meanings in different contexts. As applications grow, maintaining them becomes more challenging. Experienced developers are needed to write efficient, maintainable code and perform unit testing.

Another limitation is Python's execution speed. Since it is interpreted and dynamically typed, it performs more reference lookups, which can slow down execution. This issue can be mitigated by using alternative implementations like PyPy.

In artificial intelligence, Python is the preferred language due to its simplicity and strong community support. Libraries like TensorFlow, Keras, and scikit-learn provide tools for AI and machine learning model development. These libraries enable developers to focus on functionality rather than syntax or configuration.

The Python Package Index (PyPI) is a comprehensive repository of third-party libraries and tools developed by the Python community. PyPI allows developers to easily find, install, and use external modules for various applications.

Python's libraries and community modules support a wide range of functionalities including web and internet development, database access, GUI development, scientific and numeric computation, education, networking, and game development. Python is considered very beginner-friendly. There are extensive resources available for both programmers and non-programmers. These include beginner's guides, tutorials, installation support, and code samples to help new users get started.

The Python community is active and supportive, hosting regular conferences and workshops. Online documentation, forums, mailing lists, and IRC channels help learners and professionals collaborate and solve problems. Python is developed under an OSI-approved open-source license, making it free to use and distribute even for commercial purposes. The license is maintained by the Python Software Foundation.

Types of Machine Learning

Machine learning begins with the collection and preparation of data. This data can include numbers, text, photos, or logs such as bank transactions, sensor data, repair records, and product sales. Once the data is prepared, it is used as training data to train a machine learning model.

The more data provided to the model, the more accurate and efficient it becomes. The programmer selects an appropriate model and allows it to train on the data, identifying patterns and making predictions. Parameters can be adjusted manually to improve model performance.A portion of the data is withheld from training and is instead used to evaluate the model's accuracy. This test data helps determine how well the model performs when exposed to new, unseen inputs.

BLYNK IoT

Blynk is a platform that provides iOS and Android apps to control hardware like Arduino, Raspberry Pi, and similar devices over the Internet. It offers a digital dashboard where users can easily build graphic interfaces for their projects by dragging and dropping widgets. Setting up Blynk is extremely simple, allowing users to start creating projects within five minutes. Blynk is not restricted to any specific board or shield, making it highly versatile. It supports a wide range of hardware options, whether your Arduino or Raspberry Pi is connected via Wi-Fi, Ethernet, or the ESP8266 chip. Blynk enables you to get your hardware online and ready for the Internet of Things (IoT) environment with minimal effort.

FIG 2: BLYNK APPLICATION

Blynk is specifically designed for IoT applications. It allows users to control hardware remotely, display and store sensor data, visualize information, and perform many other advanced tasks. The Blynk platform is made up of three major components: the Blynk App, the Blynk Server, and the Blynk Libraries. The Blynk App lets users create powerful and interactive interfaces for their projects by using a variety of widgets. The Blynk Server handles all communications between the smartphone and the connected hardware, and users can either connect through the public Blynk Cloud or set up a private server locally, even on simple devices like a Raspberry Pi. The server is open-source and capable of managing thousands of devices simultaneously.

The Blynk Libraries enable seamless communication between supported hardware platforms and the Blynk Server. They manage all incoming and outgoing commands efficiently. When a user presses a button in the Blynk App, the command travels to the Blynk Cloud, which quickly relays it to the connected hardware. The same mechanism works in reverse, providing real-time interaction that feels instantaneous, occurring in just a "blynk" of an eye.

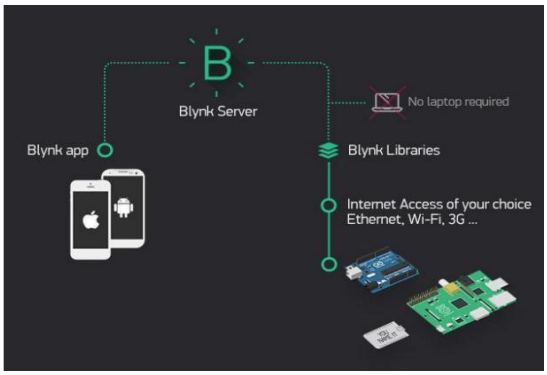

FIG 3: DATA PROCESSING

Blynk offers a consistent API and user interface across all supported hardware and devices, making it easy for developers to transition between projects. The platform allows cloud connectivity through multiple technologies including Ethernet, Wi-Fi, Bluetooth, BLE, and USB (Serial) connections. It provides a set of easy-to-use widgets that enhance project interactivity and functionality. Developers can manipulate hardware pins directly from the app without writing code, making it highly accessible to beginners. Additionally, Blynk enables the integration of new features easily through the use of virtual pins.

Another key feature of Blynk is its ability to monitor historical data through the History Graph widget, allowing users to track sensor readings and device performance over time. The platform also supports device-to-device communication via the Bridge Widget, enhancing networked device interactions. Furthermore, Blynk facilitates the sending of notifications such as emails, tweets, and push alerts directly from the app, expanding the possibilities for remote monitoring and automated reporting in IoT projects.

HARDWARE DESCRIPTIONS

ESP32 CONTROLLER

The ESP32 is a series of low-cost, low-power system-on-a-chip microcontrollers with integrated Wi-Fi and dual-mode Bluetooth capabilities. The ESP32 series utilizes either a Tensilica Xtensa LX6 microprocessor, available in both dual-core and single-core variations, or a dual-core Xtensa LX7 microprocessor, or a single-core RISC-V microprocessor. It includes built-in antenna switches, an RF balun, a power amplifier, a low-noise receive amplifier, filters, and power management modules. Developed by Espressif Systems, a Shanghai-based company, and manufactured by TSMC using a 40 nm process, the ESP32 serves as the successor to the popular ESP8266 microcontroller.

FIG 4: ESP32 CONTROLLER FEATURES

The ESP32 features a powerful processor setup with a 32-bit Xtensa dual-core (or single-core) LX6 microprocessor, operating at frequencies of 160 or 240 MHz and capable of delivering up to 600 DMIPS performance. It includes an Ultra Low Power (ULP) co-processor for energy-efficient operations. In terms of memory, the device offers 320 KiB of RAM and 448 KiB of ROM for program and data storage. The wireless connectivity of the ESP32 supports Wi-Fi standards 802.11 b/g/n and Bluetooth version 4.2, including BR/EDR and BLE, with the radio shared between Wi-Fi and Bluetooth functionalities.

The ESP32 is equipped with a wide range of peripheral interfaces. It provides 34 programmable General Purpose Input/Output (GPIO) pins, 12-bit SAR ADCs across up to 18 channels, two 8-bit Digital to Analog Converters (DACs), and ten capacitive touch sensing GPIOs. For communication purposes, the ESP32 offers four SPI interfaces, two I²S interfaces for audio processing, two I²C interfaces for sensor communication, and three UART interfaces for serial communication. It also supports storage devices through SD/SDIO/CE-ATA/MMC/eMMC host controllers and SDIO/SPI slave controllers. Networking support is enhanced with an Ethernet MAC interface featuring dedicated DMA and planned support for IEEE 1588 Precision Time Protocol.

Additional connectivity options include a CAN bus 2.0 interface and an infrared remote controller supporting up to eight channels. The ESP32 can control motors through Motor PWM and LEDs through LED PWM channels, supporting up to 16 channels. It has an integrated Hall effect sensor and an Ultra Low Power analog pre-amplifier for sensing applications.

In terms of security, the ESP32 supports all IEEE 802.11 standard security features, including WPA, WPA2, and WPA3 depending on the version. It also supports WLAN Authentication and Privacy Infrastructure (WAPI), secure boot, and flash encryption. The chip features a 1024-bit One Time Programmable (OTP) memory, with up to 768 bits available for customer applications. Cryptographic hardware acceleration is built-in for AES, SHA-2, RSA, elliptic curve cryptography (ECC), and a random number generator (RNG). Power management features are included with an internal low-dropout regulator, enhancing efficiency in various applications.

POWER SUPPLY

A power supply refers to a source of electrical power that provides energy to an output load or a group of loads. A device or system designed to supply electrical energy is known as a Power Supply Unit (PSU). Although the term is commonly applied to electrical energy supplies, it can also refer to mechanical energy supplies in some cases. Power supplies for electronic devices can be broadly categorized into linear and switching power supplies. A linear power supply is simple in design but tends to be bulky and heavy for high current applications. Voltage regulation in a linear supply often results in lower efficiency compared to switching supplies. In contrast, a switched-mode power supply is smaller, more efficient, but also more complex in design.

LINEAR POWER SUPPLY

In a linear power supply that is AC powered, a transformer is typically used to convert the wall outlet voltage (mains) to a different, often lower, voltage. If direct current (DC) is required, a rectifier is used after the transformer to convert AC to DC. A capacitor is placed to smooth the pulsating current resulting from rectification, although small periodic variations known as ripple still remain. These ripples occur at a frequency related to the AC mains frequency, typically 50 or 60 Hz. An unregulated power supply output will vary depending on the load and fluctuations in AC supply voltage. For critical electronics, a linear voltage regulator is used to stabilize the voltage, greatly reducing ripple and noise. Such regulators often provide current limiting protection, safeguarding both the power supply and connected circuitry.

Adjustable linear power supplies are often used in laboratories and service shops. They allow setting the output voltage over a wide range and are capable of providing adjustable currents. Some models can be driven by an external signal for applications requiring a pulsed output. For instance, a typical bench power supply may offer up to 30 volts and up to 5 amperes output.

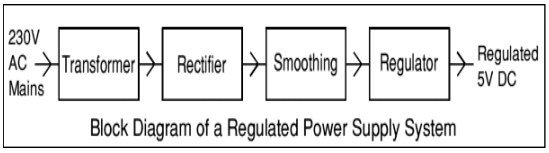

FIG 5: REGULATOR TRANSFORMER

Transformers are devices that convert AC electricity from one voltage to another with minimal loss of power. They function only with AC and are a fundamental reason why mains electricity is distributed as AC. Step-up transformers increase voltage while step-down transformers reduce voltage. Most power supplies employ a step-down transformer to decrease the hazardous 230V mains voltage to safer levels. In a transformer, the input coil is called the primary, and the output coil is called the secondary. There is no electrical connection between these coils; instead, they are linked through a magnetic field created in a soft iron core.

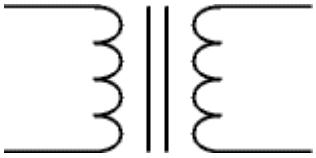

FIG 6: TRANSFORMER

Transformers are extremely efficient, with the output power closely matching the input power. As voltage decreases through a step-down transformer, current increases correspondingly. The turns ratio, which is the ratio of the number of windings in the primary to those in the secondary coil, determines the voltage ratio. The basic formula for a transformer is Vp/Vs = Np/Ns, where Vp and Vs are the primary and secondary voltages, and Np and Ns are the number of turns on the primary and secondary coils, respectively. Power conservation is expressed as Vs * Is = Vp * Ip.

The low voltage AC output from a transformer is ideal for lamps, heaters, and special AC motors. However, it is unsuitable for electronic circuits unless rectified and smoothed into DC.

RECTIFIER

Several diode configurations are used to make rectifiers that convert AC into DC. The bridge rectifier is the most important among them, producing full-wave varying DC. Although two diodes can form a full-wave rectifier when paired with a center-tap transformer, bridge rectifiers, which require four diodes, are now more common due to cost efficiency. A single diode can form a half-wave rectifier but only utilizes the positive half of the AC waveform, resulting in a less efficient DC output.

The varying DC produced by a rectifier is suitable for simple loads such as lamps and heaters, but electronic circuits require further smoothing for stable operation.

BRIDGE RECTIFIER

A bridge rectifier consists of four diodes arranged to utilize the full AC waveform, producing full-wave varying DC output. When operating, two diodes conduct during each half cycle, and about 1.4V is dropped across the bridge due to the forward voltage drop of each conducting diode. Bridge rectifiers are rated based on maximum current capacity and peak reverse voltage handling, which should be at least three times the RMS supply voltage.

Alternate diode pairs conduct during each half-cycle, allowing the AC's alternating directions to be converted into a consistent DC direction.

SINGLE DIODE RECTIFIER

Using a single diode results in half-wave rectification, where only one half of the AC cycle is utilized, creating significant gaps in the output. Smoothing such output to provide clean DC is challenging unless the current requirement is very low.

SMOOTHING

Smoothing is achieved by placing a large-value electrolytic capacitor across the DC output. This capacitor acts as a reservoir, quickly charging near the voltage peak and discharging to supply current when the rectified voltage drops. This greatly reduces voltage ripple and raises the average DC voltage close to the peak value. For example, smoothing a 6V RMS AC supply after rectification can produce a smooth DC output close to 6.4V.

However, smoothing is never perfect; a small ripple remains due to capacitor discharge. A 10% ripple is often acceptable, and the capacitance required can be calculated using the formula $C = 5 \times Io / (Vs \times f)$, where Io is the output current in amps, Vs is the peak DC voltage, and f is the AC supply frequency.

REGULATOR

Voltage regulators are used to maintain a stable output voltage despite changes in load or input voltage. Regulators are available with fixed or variable output voltages and are rated by their maximum current capacity. Positive and negative voltage regulators are available for different circuit requirements. The popular LM78XX series of fixed-voltage regulators offers reliable performance for a wide range of applications such as logic circuits, instrumentation, and HiFi systems. Many regulators provide features like overload protection and thermal shutdown.Positive voltage regulators typically have three pins: input, ground, and output, regulating a positive output voltage. Negative voltage regulators similarly have three pins but regulate negative voltages.

The regulated DC output is very smooth, free of ripple, and is ideal for powering sensitive electronic circuits.

6. RESULT ANALYSIS

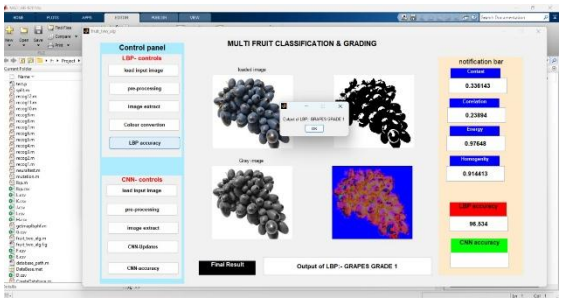

FIG 7: GRADE 1 LBP ACCURACY

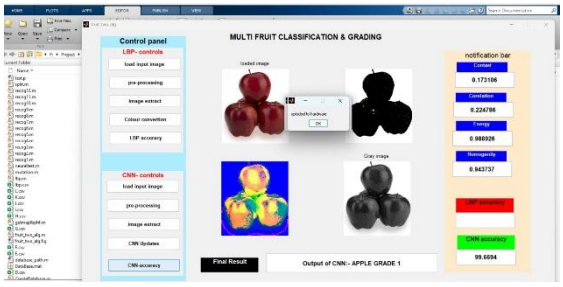

FIG 8: GRADE 1 CNN ACCURACY

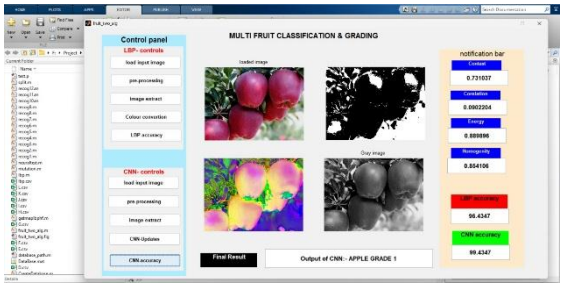

FIG 9: GRADE 1 CNN& LBP ACCURACY

7. CONCLUSION

In this project, a deep learning-based approach was developed for the classification and grading of multiple fruit types using the ResNet architecture. The traditional manual process of fruit classification, which is prone to human error and inefficiency, has been successfully automated through this system. By training the ResNet model on a labeled dataset containing various fruits and their quality grades, the system achieved reliable performance in both identifying the fruit type and evaluating its quality. The results demonstrate that deep learning models, particularly ResNet, can effectively extract relevant features from fruit images and perform accurate classification tasks. This approach significantly reduces the need for human intervention, enhances consistency in grading, and has the potential to improve quality control in the agricultural supply chain.

7.1 FUTURE ENHANCEMENT

While the current model performs well under controlled conditions, future enhancement scan further improve its accuracy and usability. One potential direction is the integration of real-time image capture using cameras or mobile devices, allowing on-the-spot grading in farms and marketplaces. Additionally, expanding the dataset to include more fruit types and environmental conditions (e.g., lighting, background variations) can make the model more robust. Another enhancement could be implementing multi-head classification, separating fruit type and grade predictions into two outputs for more flexibility. Lastly, deploying the model in the form of a mobile or cloud-based application would make it more accessible to farmers, distributors, and retailers, enabling wide-scale adoption of AI in agriculture.

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