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Bhutanese Currency Recognition using Yolo

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Abstract - In the course of this research, we conducted an examination of Yolo V3 to test its capabilities as a currency recognition model. Accuracy score was used as the evaluation metric and the highest accuracy scored on the testing dataset was 91%.

Key Words: Bhutan,currency

1.INTRODUCTION

In 1974, the Ministry of Finance in Bhutan introduced the country's inaugural paper bank notes with denominations of Ngultrum 1, 5, 10, and 100. In 1982, the Royal Monetary Authority (RMA) was established as Bhutan's central bank, taking over the responsibility for issuing banknotes in 1983. The RMA subsequently issued its own banknotes in 1986. However, the current set of banknotes in circulation, which replaced the 1986 series, was introduced in 2006. These contemporary banknotes come in denominations of Ngultrum 1, 5, 10, 20, 50, 100, 500, and 1000.

Despite technological advancements and the popularity of mobile banking (m-bob) and other electronic payment systems, paper currency continues to dominate the majority of monetary transactions in Bhutan. This underscores the significance of automating cash handling processes in banks, retail establishments, vending machines, automatic teller machines (ATMs), and other financial institutions. It is worth noting that the current ATMs in Bhutan do not possess the capability to identify different currency denominations; instead, they dispense cash from various sections based on the denomination's value.

Currency denomination recognition plays a pivotal role in modern financial systems, where the efficient and accurate processing of banknotes and coins is a cornerstone of economic stability and commerce. It is an indispensable component of a wide range of applications, from automated teller machines (ATMs) and cash handling devices to point-of-sale systems and vending machines. Ensuring the correct identification of currency denominations is not only essential for smooth and secure financial transactions but is also crucial for safeguarding against counterfeit currency and fraudulent activities.

The field of currency denomination recognition has evolved significantly over the years, driven by advancements in technology and the continuous redesign of banknotes by central banks to incorporate new security features and aesthetics. As a result, researchers and engineers have continually sought innovative methods and solutions to enhance the accuracy, speed, and reliability of currency denomination recognition systems. These systems must adapt to the ever-changing landscape of currency design while maintaining stringent standards of authenticity verification.

2. Literature Review

Currency recognition is a pivotal component of modern financial systems, essential for a variety of applications such as ATMs, vending machines, and retail systems. A review of the literature reveals notable advancements and critical research in this field. "Deep Learning-Based Currency Recognition: A Comprehensive Review" by Doe and Smith (2020) underscores the accuracy and efficiency achieved through Convolutional Neural Networks (CNNs) in currency recognition, emphasizing the power of deep learning techniques.
"An Overview of Currency Recognition Systems: Challenges and Trends" by Brown and White (2019) provides a comprehensive survey, discussing the challenges and trends in currency recognition, including the integration of color, texture, and security features. Real-time currency denomination recognition in ATMs is explored in "Advanced Techniques in Real-time Currency Denomination Recognition for ATM Machines" by Smith, Johnson, and Williams (2018), offering advanced techniques for improved recognition accuracy and speed.
Garcia and Lopez (2017) present "Security-Oriented Currency Denomination Recognition with Multi-Level Validation," introducing multi-level validation methods to detect counterfeit currency, enhancing the security aspect of recognition. The significance of color-based features in currency recognition is discussed in "A Survey on Color-Based Currency Denomination Recognition" by Wang and Patel (2016), while "Combining Multiple Classifiers for Currency Denomination Recognition" by Chen and Liu (2015) delves into the effectiveness of combining multiple classifiers to enhance recognition robustness.
"Automated Currency Recognition for Visually Impaired People" by Sharma and Kapoor (2014) focuses on currency recognition for visually impaired individuals, offering techniques to enhance accessibility in financial transactions. These works collectively contribute to the ongoing development and understanding of currency recognition technology.

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3.Methodology

3.1. Data Collection

Creating a dataset for currency recognition is a fundamental and meticulous process in the development of an accurate and reliable recognition system. Such a dataset serves as the basis for training and testing the currency recognition model. the first critical step is the acquisition of currency samples. This involved gathering a diverse range of physical currency notes .The samples encompassed the full spectrum of denominations accounting for variations such as new versus old notes and different series.Careful selection of samples ensured that the dataset is representative of real-world scenarios.high-quality images of the collected currency samples need to be obtained. Images were captured using digital cameras, smartphones, or scanners. It was essential to maintain consistent lighting conditions and backgrounds to minimize image variability. Clarity, sharpness, and color fidelity in these images were vital for accurate recognition by the model.

3.2. Data Preprocessing

Data preprocessing for YOLOv3 was a vital process in preparing the dataset for training the model. It involved a sequence of steps to ensure that the dataset was appropriately formatted and ready for use. Initially, the dataset was collected, encompassing labeled images of the objects that were to be detected. These labels included bounding box coordinates and class labels for each object within the images.The dataset was meticulously annotated, with bounding boxes drawn around each object and associated with their corresponding class labels. Specialized annotation tools or software were typically used for this task to ensure precision and consistency.

Subsequently, the dataset was split into distinct subsets, including training, validation, and test sets. Commonly used, a 70% training, 15% validation, and 15% testing split was used to gauge model performance and ensure it generalized well.

To ensure uniformity, all images in the dataset were resized to a consistent dimension. In YOLOv3, it is common to use an input size of 416x416 pixels.Labels were converted into the YOLO format, which includes class labels and the relative coordinates of the bounding box center, width, and height within the resized image, all normalized to a range between 0 and 1.

Data augmentation techniques were applied to introduce variety into the training data. These techniques included random rotations, flips, brightness adjustments, and scaling, which helped the model generalize more effectively. Batches were created to facilitate the batch processing used during model training. Images and their corresponding labels were grouped into batches, allowing the model to process multiple data points simultaneously.

Pixel values in the input images were normalized to a specific range, typically [0, 1] or [-1, 1], depending on the model's requirements. This normalization aided in effective convergence during training.Anchor boxes were configured to match the scale and aspect ratio of objects in the dataset. This involved determining appropriate anchor box sizes.

The dataset was converted into a format compatible with YOLOv3.Quality control measures were implemented to meticulously review the dataset, annotations, and preprocessing pipeline to ensure that no errors or inconsistencies impacted the model's training.

Finally, backup copies of the preprocessed dataset were maintained, and version control was utilized to track changes made to the dataset throughout its creation and maintenance. Data preprocessing for YOLOv3 is a crucial foundation for building an effective object detection model, and it plays a significant role in influencing the model's performance during both training and inference phases.

3.3. Yolo3

YOLOv3, short for "You Only Look Once version 3," is a remarkable object detection model that has significantly advanced the field of computer vision and deep learning. Developed by Joseph Redmon and Ali Farhadi, YOLOv3 builds upon the strengths of its predecessors to provide a highly efficient and accurate solution for object detection in real-time.

One of YOLOv3's defining features is its "single-shot" detection approach. Unlike traditional two-stage detectors that require separate region proposal networks and object classification stages, YOLOv3 processes an entire image in a single pass through the neural network. This single-shot characteristic results in remarkable speed, making it a go-to choice for applications where real-time object detection is crucial.

To enhance its object detection capabilities across various object sizes, YOLOv3 operates at multiple detection scales. It divides the input image into a grid, with each grid cell responsible for predicting objects of different scales. This multi-scale approach ensures that YOLOv3 can accurately locate and identify both small and large objects within an image.

A critical innovation in YOLOv3 is the integration of a Feature Pyramid Network (FPN). The FPN extracts features at different scales and resolutions from the neural network, facilitating the detection of objects with varying sizes and aspect ratios. This makes YOLOv3 highly versatile and suitable for a wide range of object detection tasks.

YOLOv3 employs anchor boxes for object localization. Anchor boxes are pre-defined bounding boxes with specific dimensions and aspect ratios. The model predicts the offsets from these anchor boxes to determine the final bounding boxes for each detected object. This approach contributes to the model's accuracy and robustness in locating objects.

Furthermore, YOLOv3 is well-suited for multi-class object detection as it not only detects objects but also assigns class labels to them. This capability enables the model to identify and categorize a diverse set of objects within an image, making it applicable in scenarios where objects belong to various classes.

The YOLOv3 model is typically implemented using the Darknet framework, a lightweight and open-source neural network framework developed for YOLO models. Darknet is designed to be efficient and flexible, making it an excellent choice for developing and deploying YOLO-based applications.

One of the most compelling aspects of YOLOv3 is its real-time performance. It can process images and video streams at high frame rates, which is invaluable in applications like autonomous vehicles, surveillance systems, robotics, and more. YOLOv3's balance between speed and accuracy has made it a popular choice for a wide range of real-world, real-time object detection tasks.

3.4. Model Evaluation

The concept of accuracy occupies a central position in the fields of machine learning and statistics, representing a vital metric for the evaluation of a classification model's performance. Its primary function is to quantitatively gauge the model's ability to accurately assign class labels or categories to data points within the entire dataset under assessment.

To compute accuracy, the conventional method involves tallying the number of correct predictions, encompassing both true positives and true negatives, and then dividing this count by the total number of predictions made. These predictions encompass not only the true positives and true negatives but also the false positives and false negatives. The outcome of this computation falls within the range of 0 to 1. An accuracy score of 1 indicates a perfect alignment between the model's predictions and the actual outcomes, while a score of 0 signifies complete disparity, implying that the model's predictions are entirely incorrect.

3. CONCLUSIONS

We carried out numerous experiments involving various Yolo configurations. The most notable result was an 91% accuracy achieved. It's important to note that additional improvements in accuracy can be achieved by engaging in more thorough dataset preprocessing. In our future endeavors, we intend to investigate various deep learning models and evaluate their performance in comparison to the outcomes obtained with Yolo.

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