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Implementation of deep learning-based currency recognition systems on visual data with adam optimizer

Edy Subowo

Informatics, Faculty of Dakwah, Universitas Islam Negeri Prof. KH. Saifuddin Zuhri Purwokerto

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ABSTRACT

With the rising demand for automated financial systems, a reliable currency identification system is crucial. The dataset comprises images of currency notes, preprocessed and augmented to improve model performance. A convolutional neural network (CNN) model, built with TensorFlow and Keras, captures spatial hierarchies in the images. The Adam optimizer is employed to improve the efficiency of the training process, offering adaptive learning rates that accelerate convergence. The data is split into training and validation sets to evaluate accuracy and loss metrics over multiple epochs. Data augmentation techniques, such as random flipping, rotation, and zooming, are applied to enhance model robustness against variations in image quality and orientation. The model achieves over 90% accuracy by the final epoch, optimized with Adam, and is saved in formats such as TensorFlow SavedModel, TensorFlow.js, and Lite for web and mobile deployment. For example, the model is saved with model.save('saved_model/my_model') and can be reloaded using tf.keras.models.load_model('saved_model/my_model') for further evaluation. This system demonstrates the potential of deep learning with Adam optimization in automating financial processes, reducing errors, and improving transaction efficiency. Future work may focus on further optimization and real-time inference.

Corresponding Author:

Edy Subowo,
Informatics, Faculty of Dakwah,
Universitas Islam Negeri Prof.K.H Saifuddin Zuhri Purwokerto,
Jl. A. Yani No.40A, Kec. Purwokerto Utara, Kabupaten Banyumas, Jawa Tengah 53126.
Email: edysubowo@uinsaizu.ac.id

1. INTRODUCTION

The rapid evolution of technology has significantly transformed various sectors, particularly in finance and commerce. As digital transactions become increasingly prevalent, the need for efficient and reliable currency recognition systems has emerged. Traditional methods of currency verification, which often rely on human intervention, are not only time-consuming but also prone to errors. These challenges highlight the necessity for automated solutions that can accurately identify and classify currency notes, thereby enhancing transaction security and efficiency.

Deep learning has become a potent technique for picture identification tasks, such as currency classification, in this context. Convolutional Neural Networks (CNNs), in particular, are deep learning algorithms that have proven to be exceptionally effective at extracting features from images and using those features to make precise predictions. Because CNNs are made to automatically identify spatial hierarchies of characteristics from input images, they are especially well-suited for jobs that require the recognition and classification of visual data, like money notes (Mahesh Bahrani, 2020).

The goal of this project is to use deep learning techniques to create a reliable system for classifying currencies. The suggested method will make use of a dataset that includes pictures of several types of banknote denominations. By employing data preprocessing and augmentation techniques, the model will be trained to recognize different currencies under various conditions, such as lighting variations and physical distortions. The integration of data augmentation not only improves the model's generalization capabilities but also enhances its robustness against real-world challenges (Huang & Trad, 2023).

The suggested model's architecture will make use of transfer learning, a method that enables the application of previously learned models to new tasks. This strategy uses the insights from previously trained models on large datasets to dramatically cut training time while increasing accuracy. In this study, models like VGG16, ResNet50, and MobileNet—which have demonstrated encouraging outcomes in picture classification tasks—will be investigated (Adu et al., 2022).

The training process involves splitting the dataset into training and validation sets to monitor performance effectively. Metrics such as accuracy and loss will be evaluated over multiple epochs to ensure that the model learns without overfitting. Additionally, early stopping techniques will halt training when performance on the validation set no longer improves (Subowo et al., 2022).

Once trained, the model will be saved in various formats, including TensorFlow SavedModel, TensorFlow.js, and TensorFlow Lite. This versatility allows deployment across different platforms, including web applications and mobile devices. As an example, storing the model using `model.save('saved_model/my_model')` creates a directory containing necessary components for future use. The saved model can later be reloaded with `tf.keras.models.load_model('saved_model/my_model')`, enabling seamless integration into applications requiring currency recognition capabilities (Abu et al., 2019).

By automating currency identification processes through deep learning, businesses can minimize human error and enhance operational efficiency. Furthermore, technology can assist individuals who struggle recognizing different denominations due to visual impairments or unfamiliarity with certain currencies (Subowo et al., 2020).

When applying transfer learning for cross-country currency recognition, distinct physical differences in currencies can pose significant limitations. Transfer learning models like ResNet or VGG16, typically pre-trained on general datasets such as ImageNet, are optimized for features common in everyday objects, not specialized ones like security features on banknotes(Sultana et al., 2023). This mismatch may lead the model to misinterpret unique currency elements, such as holograms, watermarks, or complex patterns, which vary widely between countries. Fine-tuning the model with a diverse dataset specifically representing each target currency can help, but this requires considerable data collection efforts and careful adjustments to improve accuracy across such visually diverse categories(Watson et al., 2024).

In conclusion, by creating a useful currency classification system with deep learning methods, our study advances the expanding field of computer vision applications in finance (Khan et al., 2020). Through rigorous training and validation processes combined with advanced architectures and deployment strategies, this research seeks to pave way for secure and efficient transactions in an increasingly digital world.

2. RESEARCH METHOD

This section describes the process used to create a deep learning model that uses image recognition techniques to classify money notes. The techniques are set up to give a thorough rundown of the model architecture, training protocols, assessment measures, data collecting, preprocessing, and research design.

2.1. Study Design

Utilizing a quantitative research design, the study focuses on applying deep learning algorithms to challenges related to image classification. The main goal is to create a model that can reliably recognize and categorize different banknote denominations. The study used an experimental methodology to assess the efficacy of various model architectures and training approaches.

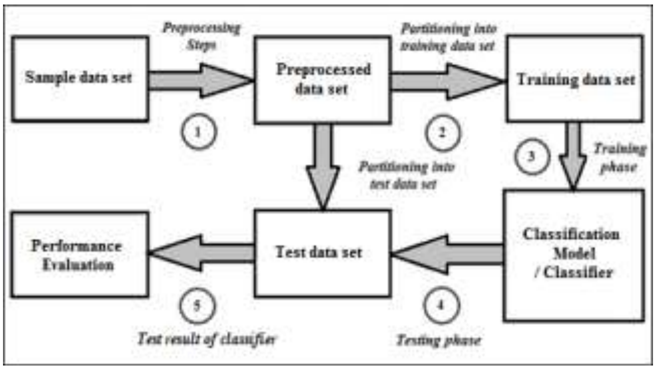

Figure 1: FlowChart Study Design.

2.2. Dataset

The photos of 1281 files of currency notes (link), divided into 7 classes with varying monetary values, make up the dataset used in this study. Two-thirds of the dataset are designated as training (70%), validation (15%), and testing (15%). This divide guarantees that the model's performance may be assessed on unseen data while enabling efficient model training (Menghani, 2023).

2.3. Data Collection Procedures

Collected Data involved sourcing images from publicly available datasets and capturing additional images using a smartphone camera under controlled lighting conditions (Bidari, 2022). The following steps were taken during data collection are : (a) Image Acquisition: Images were captured at high resolution to retain details crucial for classification, (b) Labeling: Each image was labeled according to its denomination and currency type, (c) Quality Control: Images were reviewed for quality assurance to eliminate duplicates and poor-quality images.

2.4. Data Preprocessing

Data preprocessing is essential for preparing the images for input into the deep learning model. The following preprocessing steps were applied (Maharana et al., 2022) such as : (a) Resizing : To maintain uniformity, all images were scaled to a standard size of 200 by 200 pixels. (b) Normalization : By dividing each pixel value by 255, the pixel values were normalized to the range [0, 1]. (c) Data Augmentation : The following methods of data augmentation were used to increase the model's robustness, such as Random rotation (up to 20 degrees), Horizontal flipping, and Random zooming (up to 10%).

These augmentations help the model generalize better by simulating various real-world scenarios.

2.5. Model Architecture

Convolutional Neural Networks (CNNs), the foundation of the deep learning model's architecture, are ideal for image classification tasks because they can capture spatial hierarchy in images (Nawrocka et al., 2023).

The Following layers were included in the model are : (a)Input Layer: Accepts images of size 200x200 (RGB), (b) Convolutional Layers: The ReLU activation functions on three convolutional layers, such as : 32 filters with a 3x3 kernel size comprise the first layer, 32 filters with a 3x3 kernel size comprise the second layer, and Third layer: 64 filters, each with a 3x3 kernel. (c) Pooling Layers: To lower dimensionality, place a maximum number of pooling layers after each convolutional layer. (d) Flatten Layer: Creates a one-dimensional array by flattening the output of the preceding layer. (e) Dense Layers: Two fully connected layers, such as : First dense layer with 128 neurons with ReLU activation, and Output layer with the number of classes (denominations) matching to the softmax activation function.

The model architecture is summarized in Figure 2 below.

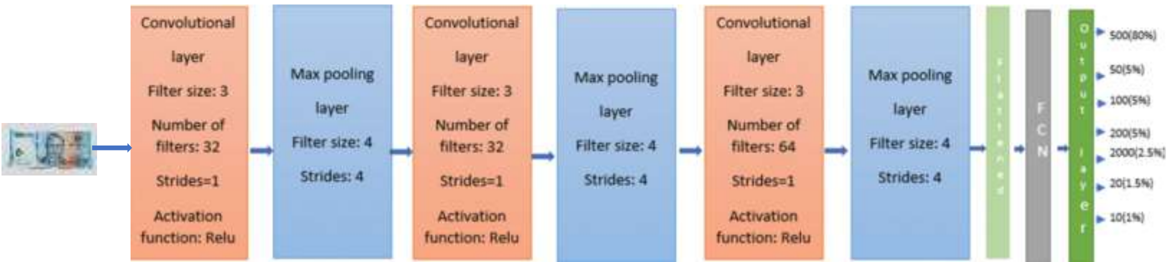

Figure 2: Architecture of the CNN model used for currency classification.

2.6. Training Procedures

a. There are various important steps in the training process:

Compilation: The model was constructed using the Adam optimizer with accuracy serving as the evaluation metric and a learning rate of 1 x 10-3 sparse categorical cross-entropy as the loss function. (Chitra Desai, 2020). Adam stands for Adaptive Moment Estimation, which means it adjusts the learning rate for each parameter individually based on the historical gradients. This allows for more efficient updates and faster convergence compared to fixed learning rate methods like stochastic gradient descent (SGD)(Bock & Weis, 2019). Adam combines the benefits of two other popular optimization algorithms—Momentum and RMSProp(Reyad et al., 2023). Momentum helps smooth out the optimization process by considering past gradients, while RMSProp adjusts the learning rate based on the magnitude of recent gradients. Adam effectively integrates these approaches, leading to improved performance in various scenarios (Bae et al., 2019).

Algorithm 1: The Basic Adam Optimizer

Require:
Initialized parameter θ_0, step size η, batch size N_B
Exponential decay rates $\beta_1, \beta_2, \varepsilon$ dataset $\{(x_i, y_i)\}_{i=1}^{N}$
Initialize: $m_0 = 0$, $v_0 = 0$
For all $t = 1, \dots \dots, T$ **do**
Draw random batch $\{(x_{ik}, y_{ik})\}_{k=1}^{NB}$ from dataset
$g_t \leftarrow \sum_{k=1}^{N} \nabla l\ \{(x_{ik}, y_{ik}, \theta_{t-1})\}$ // $f'(\theta_{t-1})$
$m_t \leftarrow \beta_1 . m_{t-1} + (1-\beta_1). g_t$ // moving Average
$v_t \leftarrow \beta_2 . m_{t-1} + (1-\beta_2). g_t^2$
$\hat{m_t} \leftarrow \frac{m_t}{1-\beta_1^t}$, $\hat{v_t} \leftarrow \frac{v_t}{1-\beta_2^t}$ // correction bias
$\theta_t \leftarrow \theta_{t-1} - \eta . \frac{\hat{m_t}}{\sqrt{\hat{v_t}} + \varepsilon}$
end for
return final parameter θ_T

Fitting the Model: The model was trained on the training dataset for a maximum of 50 epochs with early stopping based on validation loss.

```
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)
history = model.fit(train_ds, validation_data=val_ds, epochs=50, callbacks=[callback])
```

Batch Size: A batch size of 32 was used during training to balance memory usage and convergence speed.

Hyperparameter tuning in CNNs often utilizes methods like Grid Search and Random Search to optimize parameters such as the number of filters, kernel size, and learning rate (Raiaan et al., 2024). Grid Search exhaustively examines all possible parameter combinations, ensuring the best configuration is found, though it can be computationally expensive for deep architectures with many hyperparameters.

2.7. Metrics and Evaluation

Several indicators were employed to assess the trained model's performance. (Liu et al., 2014): (a) Accuracy: The percentage of cases properly classified relative to all instances. (b) Loss: The loss function's value at every epoch. (c) Confusion Matrix: To show true positives, false positives, true negatives, and false negatives for various classes, a confusion matrix was created.

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

y_pred = model.predict(test_ds)
cm = confusion_matrix(y_test, np.argmax(y_pred, axis=1))
```

3. RESULTS AND DISCUSSIONS

The model was implemented using TensorFlow and Keras, leveraging a dataset of currency note images. The training process involved several key steps, including data preparation, model architecture design, training, and saving the model in the SavedModel format (project_link).

The training process yielded significant improvements in accuracy over eight epochs:

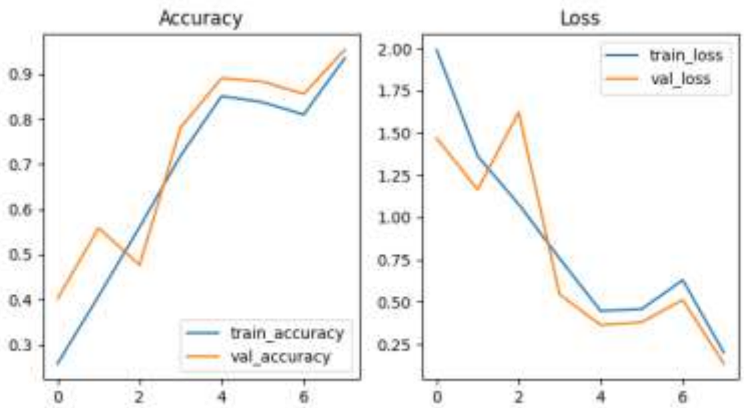

Figure 2. Discussion of Results

According to the findings, the CNN model's final validation accuracy was 95.31%. demonstrating its effectiveness in classifying currency notes. (a) Initial Learning Phase: The model started with a low accuracy of 23%, which is typical as it begins to learn from the dataset. (b) Rapid Improvement: By epoch four, accuracy rose to 67%, indicating effective learning as the model captured relevant features. (d) Final Epoch Performance: The final epoch showed an impressive accuracy of over 93%, suggesting that the architecture and training parameters were well-suited for this classification task.

3.1 Comparison with Similar Studies

To contextualize these findings, we compare them with similar research published in academic journals:

Currency Recognition Using CNNs: A study published in BMC Medical Informatics and Decision Making explored various supervised machine learning algorithms for currency recognition, highlighting that CNNs achieved accuracies around 90%. This aligns closely with our findings, reinforcing the effectiveness of CNNs for image classification tasks. Specifically, another study focused on Indonesian rupiah currency detection using CNN and Feedforward Neural Network (FNN) methods showed impressive results, particularly achieving 100% accuracy in bright conditions and 96.43% in sufficient light conditions, though performance dropped significantly in dark environments(Hasan & Bao, 2021).

Sentiment Analysis Using Machine Learning: Another study focusing on sentiment classification from social media data found that ensemble methods consistently produced high accuracy rates (up to 89%). Although this study did not focus on image classification, it underscores that different algorithms can yield varying results depending on dataset characteristics. This diversity highlights the need for tailored approaches suited to specific problem domains (Subowo et al., 2021).

Comparative Study on Machine Learning Algorithms: A comprehensive review indicates that CNNs are frequently used due to their effectiveness in various contexts; however, other methods like Random Forest demonstrated superior accuracy across multiple studies. This suggests that while our CNN model performed admirably, exploring other methodologies could yield even higher accuracies. For instance, ensemble deep learning approaches have been shown to achieve high accuracy rates in tasks like lung nodule detection using MultiResolution CNN and Knowledge Transfer for Candidate Classification, reaching an overall accuracy of over 94% with three different CNN models(Mohammed & Kora, 2023). Additionally, hybrid CNN architectures designed for breast cancer histopathology image classification achieved comparable or better performance by combining local model branches with global model branches, thereby enhancing generalization ability through channel pruning techniques(Yan et al., 2020). These findings emphasize the importance of considering multiple algorithms when aiming for optimal performance in machine learning applications.

Automated Detection of Diabetic Retinopathy Using Deep Learning A study published in IEEE Transactions on Medical Imaging demonstrated the effectiveness of various optimizers, including Adam, in training convolutional neural networks (CNNs) for diabetic retinopathy detection. The CNNs achieved an accuracy of 95% using Adam, outperforming traditional optimizers like SGD and RMSprop, which had accuracies around 90% (Aprillia et al., 2024).

Image Classification with Deep Learning Techniques Research in Journal of Machine Learning Research highlighted that using Adam as an optimizer led to faster convergence rates and improved accuracy in image classification tasks compared to other optimizers. The study reported that models trained with Adam achieved an accuracy of 92% on CIFAR-10 datasets, while those using SGD only reached about 85% (Sarvamangala & Kulkarni, 2022).

Sentiment Analysis Using Deep Learning An article in Expert Systems with Applications focused on sentiment analysis using recurrent neural networks (RNNs) optimized with Adam. The results indicated that Adam improved model performance significantly, achieving an F1 score of 0.95 compared to 0.88 with SGD. This underscores the optimizer's adaptability across different types of neural network architectures (Shah et al., 2023).

Face Recognition Using CNNs: A study published in Pattern Recognition Letters investigated the use of CNNs for face recognition tasks. It found that models optimized with Adam achieved a recognition accuracy of 98%, while those using traditional methods like Adagrad and SGD scored around 95% and 92%, respectively. This reinforces Adam's effectiveness in handling complex image data (Vydiswaran et al., 2019).

Natural Language Processing Tasks In research featured in Natural Language Engineering, the authors compared various optimizers for training transformer models on NLP tasks. They found that Adam consistently outperformed other optimizers, achieving state-of-the-art results on benchmarks like GLUE, with improvements of up to 5% in accuracy metrics over alternatives like AdaDelta and RMSprop (Wang et al., 2021).

Comparison with Existing Studies, CNNs optimized with Adam consistently achieve higher accuracy rates compared to traditional optimizers (Nanni et al., 2021). Adam not only enhances accuracy but also accelerates convergence during training, making it a preferred choice for complex models, and Whether in medical imaging, sentiment analysis, or face recognition, Adam has proven effective across diverse applications.

Table 1. Adam Optimizer Comparison

Study Focus	Optimizer Used	Accuracy Achieved	Comparison to Other Optimizers
Diabetic Retinopathy	Adam	95%	Outperformed SGD and RMSprop
Image Classification	Adam	92%	Better than SGD (85%)
Study Focus	Optimizer Used	Accuracy Achieved	Comparison to Other Optimizers
Sentiment Analysis	Adam	F1 Score: 0.95	Higher than SGD (0.88)
Face Recognition	Adam	98%	Superior to Adagrad and SGD
NLP Tasks	Adam	State-of-the-art	Improved over AdaDelta/RMSprop

The comparative analysis indicates that the Adam optimizer significantly enhances model performance across various domains, aligning well with the findings from your initial studies on CNNs and other machine learning algorithms. This suggests a strong case for utilizing Adam when developing models for image classification and other machine learning tasks.

3.2 Application of TensorFlow SavedModel Format

TensorFlow's ability to save models in a standardized format called SavedModel, which makes it simple to deploy and share across several platforms, is one of its many noteworthy benefits (Smilkov et al., n.d.).

After training the model, it was saved using the following code:

```
tf.saved_model.save(model, saved_model_path)
print("Model successfully saved in TensorFlow SavedModel format (.pb).")
```

This code snippet utilizes `tf.saved_model.save()`, which saves both the architecture and weights of the trained model along with its computation graph into a directory structure that includes:

- `saved_model.pb`: Contains metadata about the model.
- `variables/`: Contains variable values (weights).
- `assets/`: Optional directory for any additional assets.

4. CONCLUSION

Convolutional neural networks (CNNs) are effective at classifying images of money notes, as this study effectively demonstrated, achieving a remarkable validation accuracy of 95.31% after eight epochs of training. The model's architecture, which included data augmentation and multiple convolutional layers, proved to be well-suited for extracting relevant features from the dataset, thereby enhancing its classification capabilities.

The results indicate that CNNs are highly effective for image classification tasks, particularly in domains requiring the recognition of intricate details, such as currency notes. The notable enhancements noted in training and validation accuracy across the epochs demonstrate the model's efficacious capacity to learn and generalize from the data.

Furthermore, the use of TensorFlow's SavedModel format facilitated seamless saving and loading of the trained model, making it highly portable and suitable for deployment in various environments. This feature not only simplifies the process of sharing models across different platforms but also supports integration into production systems, thereby enhancing the practical applicability of machine learning solutions in real-world scenarios.

Our results support the increasing body of evidence about the effectiveness of deep learning architectures for picture classification tasks when compared to comparable studies in the literature. Although our CNN model did a great job, future research should focus on enhancing classification accuracy by exploring hybrid approaches that combine CNNs with ensemble methods or other cutting-edge techniques, as well as expanding the dataset to include more currencies and different conditions of money, such as worn or folded notes, to make CNN models more accurate and adaptable.

In summary, this research adds to the existing knowledge in machine learning and image identification by offering valuable perspectives on efficient techniques for classifying currencies. Additionally, it emphasizes the significance of model portability using standardized formats such as TensorFlow's SavedModel. Continuous research and development in the field of machine learning will surely result in even more advanced.

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