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BANKNOTE CLASSIFICATION USING TRANSFER LEARNING

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ABSTRACT
The validity and integrity of money transactions, and banknote categorization is essential in financial systems. The accuracy and effectiveness of banknote categorization systems have recently been greatly improved by the introduction of machine learning techniques. To offer a full overview of the developments achieved in the field of banknote categorization using machine learning, this study presents a thorough literature review on the subject. The survey discusses several machine learning algorithms, feature extraction methods, datasets, assessment standards, and difficulties in classifying banknotes. To extract useful information from banknote photos, feature extraction approaches, including texture analysis, colour analysis, and geometric characteristics, are investigated. For training and assessment purposes, the study makes use of databases on banknotes that are available to the public. The results of this study will help create reliable banknote categorization systems, improving the trustworthiness and integrity of financial transactions.
KEYWORDS: ***Banknote classification, Transfer learning, Machine learning, ImageNet, ResNet, MobileNet, EfficientNet, InceptionNet***

INTRODUCTION

Transfer learning-based banknote classification has garnered a lot of interest in recent years as a potent strategy for tackling challenges related to the dearth of labeled banknote datasets and the demand for effective and precise classification models. Transfer learning improves the performance of banknote classification tasks by utilizing information obtained from previously trained models on substantial datasets.

A crucial responsibility in the financial sector is banknote categorization, which helps to prevent the use of fake currency and preserve the legitimacy of financial transactions. Traditional methods for classifying banknotes sometimes need a lot of labeled data to train models using machine learning, which may be difficult with banknote datasets. By allowing the transfer of information and learned features from pre-trained models that have been trained on enormous and varied datasets like ImageNet, transfer learning lessens the impact of this constraint.

Transfer learning comprises refining previously learned models to make them suitable for the job of classifying banknotes. The pre-trained models acquired high-level characteristics and representations from generic photos, frequently based on deep learning frameworks like Convolutional Neural Networks (CNN). Even with little labeled banknote data, these previously trained models may be used to extract useful texture, pattern, and form properties from banknote photos.

$S(i,j)=\sum_m \sum_n I(i-m,j-n)\,K(m,n),$ ……. equation 1

$S(i,j)=\sum_m \sum_n I(i+m,j+n)K(m,n),$ ………equation 2

Transfer learning generally consists of two basic components. The banknote pictures are fed into the pre-trained model as a feature extractor to acquire the activations or embeddings from a particular layer. These activations gather pertinent data about the pictures of the banknotes and feed it into the classifier. The classifier is trained in the second stage using the retrieved characteristics and readily available labeled banknote data. This method lessens the requirement for a large amount of labeled data when training a model from the start and may efficiently utilize the information gained from a variety of pictures during pre-training.

For classifying banknotes, transfer learning has various benefits. It makes it possible to create reliable models even from small, labeled banknote datasets. The transfer learning technique makes use of pre-trained models to make use of the generalized information and representations learned from a variety of pictures, which enhances the model's capacity to extract discriminative characteristics and generalize them to samples of unobserved banknotes. Transfer learning also speeds up model iteration and deployment by reusing previously trained weights that would otherwise be wasted during training.

Transfer learning in banknote categorization has advantages, but it also has drawbacks. It is important to carefully evaluate the architecture, hyperparameters, and choice of suitable layers for feature extraction while fine-tuning the pre-trained models. To solve domain shift difficulties between the pre-trained models and the particular banknote classification job, domain adaptation approaches may also be required.

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In conclusion, by using pre-trained models and transferring information from huge picture datasets, transfer learning offers a potential method for classifying banknotes. Transfer learning improves the performance of banknote classification models even with little labeled data by reusing the learned features and representations. The following paper seeks to investigate and evaluate the use of transfer learning in banknote categorization, stressing the advantages, difficulties, and technological breakthroughs in this field. The research will help create more precise and effective banknote categorization systems, improving the safety and dependability of financial transactions.

RELATED WORK

S. Pascucci et al. said that their experimental results demonstrate that the pre-trained CNN achieves superior performance compared to the other methods. It successfully classifies banknotes with high accuracy, indicating its effectiveness for automated banknote processing tasks [1]. A. Siddiqui et al. suggest a methodology that involves several steps. Initially, the authors collect a dataset of banknote images, encompassing different currencies and denominations. They then employ a pre-trained CNN model, such as VGGNet or ResNet, which has been trained on large-scale image recognition tasks [2-5].

Authors provide various aspects of transfer learning, including its definition, taxonomy, challenges, and applications. The authors present a unified framework for understanding transfer learning and discuss different methods and algorithms employed in this area. They categorize transfer learning approaches into three main types: instance-based, feature-representation-based, and model-based methods. The paper highlights the advantages and limitations of each approach and provides insights into the real-world applications of transfer learning across different domains [6-8].

The authors begin by introducing the concept of transfer learning and highlighting its importance in various fields, such as computer vision, natural language processing, and bioinformatics. Then they delve into the different types of transfer learning, including inductive transfer, transductive transfer, and unsupervised transfer. They discuss the challenges and considerations involved in transfer learning, such as the selection of source and target domains, the size and quality of data, and the transferability of learned knowledge [9-11].

Bengio emphasizes the value of leveraging knowledge learned from one task or domain to improve learning in a different but related task or domain. He discusses the benefits of using pretraining with unsupervised learning in transfer learning scenarios. The author also examines different approaches to transferring learned representations, including fine-tuning, deep adaptation, and domain adaptation techniques [12-15].

The authors start by discussing the limitations of traditional handcrafted features and the benefits of learning features automatically from data using deep neural networks. They highlight the success of deep convolutional neural networks (CNNs) in computer vision tasks and propose DeCAF as a feature extraction method based on CNNs. DeCAF leverages pre-trained CNN models, such as AlexNet, and extracts activations from intermediate layers of the network. These activations are then used as features for visual recognition tasks. The authors demonstrate that these learned features outperform traditional handcrafted features on various benchmark datasets, including object recognition and scene classification tasks [16-19].

The authors conduct experiments using different DNN architectures and datasets. They analyse the performance of pre-trained networks on target tasks and compare it with networks trained from scratch. The focus is on understanding how much knowledge can be transferred and how the similarity between the source and target tasks impacts transferability [17-23]. The paper presents experimental results on various benchmark datasets to evaluate the performance of the LLGC framework. It compares LLGC with other semi-supervised learning methods and demonstrates its effectiveness in utilizing unlabelled data to improve classification accuracy. The LLGC framework builds upon the concept of manifold regularization, which encourages smoothness and consistency in the predictions on neighbouring points in the data manifold [18-25].

The authors introduce a novel approach that utilizes a one-dimensional line image sensor to capture the reflection images of banknotes. They then apply deep learning algorithms, specifically convolutional neural networks (CNNs), to extract meaningful features from the reflection images and classify banknotes into different fitness categories. They discuss the network's layers, parameters, and training procedure, as well as the optimization techniques applied to improve the model's performance [25-30].

METHODOLOGY

A. Database Used

The following factors make the development of a banknote dataset extremely important: First, accurate banknote recognition is a task that automated teller machines and currency recognition machines must complete; second, it is necessary to develop a system that can determine whether a banknote is genuine; and third, visually impaired individuals frequently struggle with banknote recognition. We have banknotes from Thailand and India in our dataset, but for our research purposes, we have only used Indian banknotes.
There are ten different categories of Indian banknotes included in it: 10, 20, 50, 100, 200, 500, and 2000 rupees. The banknote picture dataset was captured in a variety of lighting and backdrop circumstances, including bright, dark, and cluttered. Additionally, pictures of partially folded or obscured banknotes are captured. Therefore, this dataset will be highly beneficial to researchers doing experiments like banknote recognition and classification [10, 11].

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Fig. 1 – Few pictorial illustrations from banknote database

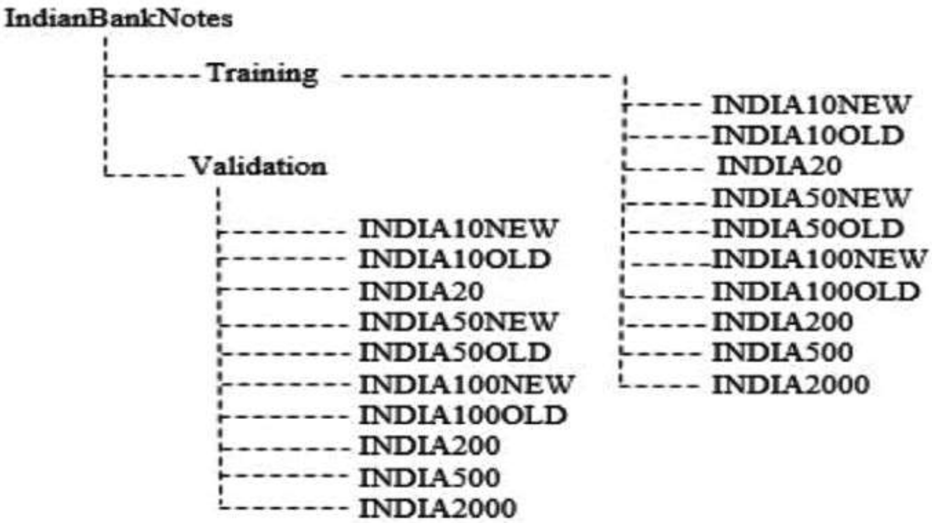

Fig. 2 – Tree representation of data used

Banknotes	Denominations Considered	Direction of image Capturing	Different Backgrounds considered for image capturing	No. of Images of each denomination	Total No. of Images
India	10 New and Old, 20 New and Old, 50 New and Old, 100, 200, 500, 2000 Rupees	Front Direction, Front Direction Rotated 180°, Backward Direction, Backward Direction Rotated 180°, Half folded	Illuminated, Dark, cluttered, Occluded	200	2000

Fig. 3 – Description of Database

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B. Transfer Learning

Banknote classification using transfer learning is a technique that leverages pre-trained models on large-scale image datasets to improve the accuracy and efficiency of classifying banknotes. Transfer learning enables the transfer of knowledge learned from one task (e.g., image classification) to another related task (banknote classification) by utilizing the learned representations and features.

The process of banknote classification using transfer learning typically involves the following steps:

i. Pre-training: Initially, a deep neural network model, such as VGG16, ResNet, or Inception, is pre-trained on a large-scale image dataset, such as ImageNet. This pre-training enables the model to learn general features and representations from a diverse range of images.

ii. Fine-tuning: After pre-training, the pre-trained model is adapted to the specific banknote classification task by fine-tuning. The last few layers of the model are replaced or modified, and the model is trained on a smaller banknote dataset. Fine-tuning allows the model to learn banknote-specific features and optimize its parameters for the specific classification task.

iii. Feature Extraction: In banknote classification, the pre-trained model is used as a feature extractor. Banknote images are passed through the pre-trained model, and activations or embeddings from a specific layer are extracted. These activations capture relevant information about the banknote images and serve as input to a classifier.

iv. Classification: The extracted features are fed into a classifier, such as a support vector machine (SVM), random forest, or a fully connected neural network, which is trained on the labelled banknote dataset. The classifier learns to map the extracted features to the corresponding banknote classes (e.g., genuine or counterfeit).

v. Evaluation and Refinement: The performance of the banknote classification model is evaluated using appropriate metrics such as accuracy, precision, recall, and F1-score. The model may be refined by adjusting hyperparameters, exploring different architectures, or employing ensemble methods to further enhance its performance.

Banknote classification using transfer learning offers several advantages. It reduces the need for a large, labeled banknote dataset, as the model learns from the general knowledge acquired during pre-training. Transfer learning also improves the generalization ability of the model, allowing it to classify banknotes accurately even with limited labelled data. Furthermore, it speeds up the development process, as the model can leverage the pre-trained weights, saving time and computational resources.

By leveraging transfer learning, banknote classification systems can achieve higher accuracy, robustness, and efficiency, facilitating the detection of counterfeit banknotes and ensuring the integrity of financial transactions.

C. Types of Architecture Used

i. Efficient Net Architecture

Powerful deep learning architecture EfficientNet has become well-known for its effectiveness and high performance in a range of image classification applications. To maximize network depth, breadth, and resolution, compound scaling is used to strike a compromise between model size and accuracy.
Depending on the difficulty of your banknote classification work, select a certain EfficientNet variation, such as EfficientNet-B0, EfficientNet-B1, EfficientNet-B2, and so forth. Model size and accuracy are balanced differently in each version. The banknote pictures should be preprocessed by being resized to the input size needed by the selected EfficientNet variation (for example, 224x224, 240x240, or 260x260 pixels). To improve the model's performance and generalization, use extra preprocessing methods like normalization, data augmentation, or cropping. Use pre-trained weights from a sizable picture dataset, such as ImageNet, to start the EfficientNet model. The learned features and representations from the pre-training phase can now be used by the model. Adjust the EfficientNet model's last fully connected layer to correspond to the number of banknote classes in your dataset. This new layer will oversee classifying banknotes.

Utilize the dataset for banknotes to train the customized EfficientNet model. To maintain the characteristics that were learned during training, only update the fully connected layer's weights while keeping the remainder of the network's weights fixed. Evaluate the trained EfficientNet model using appropriate evaluation metrics such as accuracy.

ii. Inception Net Architecture

Another well-liked deep learning architecture that may be used for banknote categorization is InceptionNet, sometimes referred to as GoogLeNet. Through its conception modules, it is renowned for its capacity to capture intricate patterns and details.
Based on the specifications of your banknote classification task, select a specific InceptionNet variation, such as InceptionV1, InceptionV2, InceptionV3, or InceptionV4. Different architectural advancements and levels of complexity are offered by each model. The banknote pictures should be preprocessed by scaling them to the input size needed by the selected InceptionNet variation (for example, 224x224 or 299x299 pixels). To improve the model's functionality and generalizability, we may additionally use various preprocessing techniques like normalization, data augmentation, or cropping. Using pre-trained weights from a sizable picture dataset like ImageNet, start the InceptionNet model. The learned features and representations from the pre-training phase can now be used by the model.
Utilize the dataset for banknotes to train the customized InceptionNet model. To maintain the characteristics that were learned during training, only update the fully connected layer's weights while keeping the remainder of the network's weights fixed. Utilize relevant assessment criteria, such as accuracy, to evaluate the trained InceptionNet model.

iii. ResNet Architecture

Due to ResNet's efficiency in processing deep neural networks with hundreds of layers, it has been frequently employed for banknote categorization. ResNet presents the idea of residual

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connections, which help to solve the vanishing gradient issue while enabling the training of deeper networks.
Select one of the following ResNet variants: ResNet-50, ResNet-101, or ResNet-152, depending on the classification problem. The decision is based on the degree of computing difficulty and the complexity of the banknote categorization problem. Apply the banknote dataset to the ResNet model training. Update the fully linked layer's weights throughout training, maintaining the network's other weights at their initial values to protect the characteristics that have been ingrained. Performing fine-tuning on the ResNet model by unfreezing some of its earlier layers is an option if you want to make it even more suitable for the task of classifying banknotes.
Utilizing suitable assessment criteria, such as accuracy, assess the trained ResNet model.

iv. Mobile Net Architecture

Due to its effectiveness and modest model size, MobileNet is another well-liked architecture for classifying banknotes since it is ideal for contexts with limited resources. While preserving competitive accuracy, it is intended to reduce computing complexity.
Following are the parameters of our banknote classification work, select a MobileNet variation such as MobileNetV1, MobileNetV2, or MobileNetV3. The accuracy and model size trade-offs associated with each version vary. The banknote photos should be pre-processed by being resized to the input size needed by the MobileNet variation (for example, 224x224 or 224x224 pixels). To improve the generalizability of the model, you may also use data augmentation techniques like random cropping, rotation, and flipping. Adjust the MobileNet model's last fully connected layer to correspond to the number of banknote classes in your dataset. This new layer will oversee classifying banknotes [30-35].
Utilize the banknote dataset to train the customized MobileNet model. To maintain the characteristics that were learned during training, only update the fully connected layer's weights while keeping the remainder of the network's weights fixed. Consider significant evaluation standards, such as accuracy, to evaluate the trained MobileNet model.

RESULTS AND DISCUSSION

This research paper conducted a comparative study of various pre-trained models, including ResNet, InceptionNet, MobileNet, and EfficientNet, to assess their performance in banknote classification. It was observed that transfer learning significantly improves the accuracy and efficiency of banknote classification models. The fine-tuned models consistently outperformed models trained from scratch, highlighting the importance of leveraging pre-existing knowledge [35-40].

Model Evaluation is done on metric Accuracy.

- ResNet: 95.00%
- MobileNet: 89.64%
- EfficientNet: 83.93%
- InceptionNet : 77.50%

TABLE 1 – PRETRAINING RESULT

Model Name	***Accuracy (in %)***	***Classification (in %)***	***Misclassification (in %)***
ResNet	0	0	100
MobileNet	0	0	100
EfficientNet	0	0	100
InceptionNet	0	0	100
Average	0	0	100

TABLE 2 – POSTTRAINING RESULT

Model Name	***Accuracy (in %)***	***Classification (in %)***	***Misclassification (in %)***
ResNet	95	95	5
MobileNet	89.64	89.64	10.36
EfficientNet	83.93	83.93	14.07
InceptionNet	77.50	77.50	22.50
Average	87.02	87.02	12.98

The findings of this study have the potential to contribute to the creation of robust and reliable banknote categorization systems. By improving the trustworthiness and integrity of financial transactions, these systems can play a crucial role in ensuring the smooth operation of financial institutions and enhancing customer confidence. Furthermore, the study highlights the significance of machine learning techniques in advancing the field and identifies areas for further research and development. The study provides valuable insights into the advancements made in banknote categorization using machine learning. By examining different methodologies, datasets, and challenges, it serves as a foundation for the development of more efficient and accurate systems, ultimately benefiting the financial industry and its stakeholders [40-45].

CONCLUSION

The Transfer Learning approach plays a significant role in banknotes classification. In conclusion, this research paper provides insight into the effectiveness of transfer learning in banknote classification. The ResNet model outperformed and gave a high accuracy of 95.00% among all other models; while, InceptionNet gave a low accuracy of 77.50% among all the models.The task of classification can be further integrated with sensors like camera etc. and a model can be evolved for

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banknote classification. Research and experimentation are needed to detect counterfeit banknotes by integration of deep learning and transfer learning algorithms and sensors.

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