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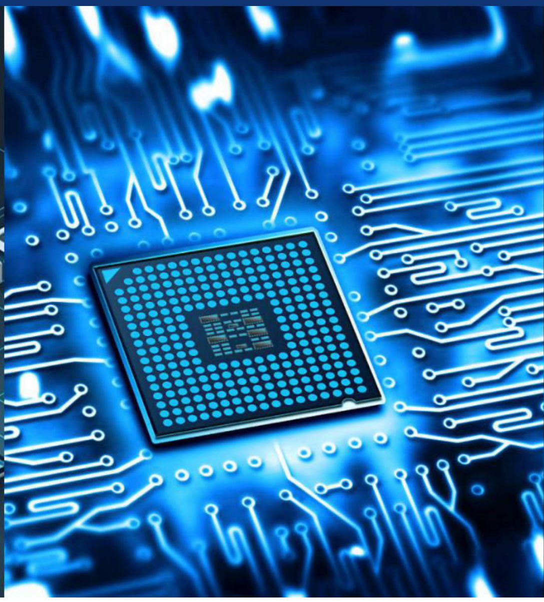

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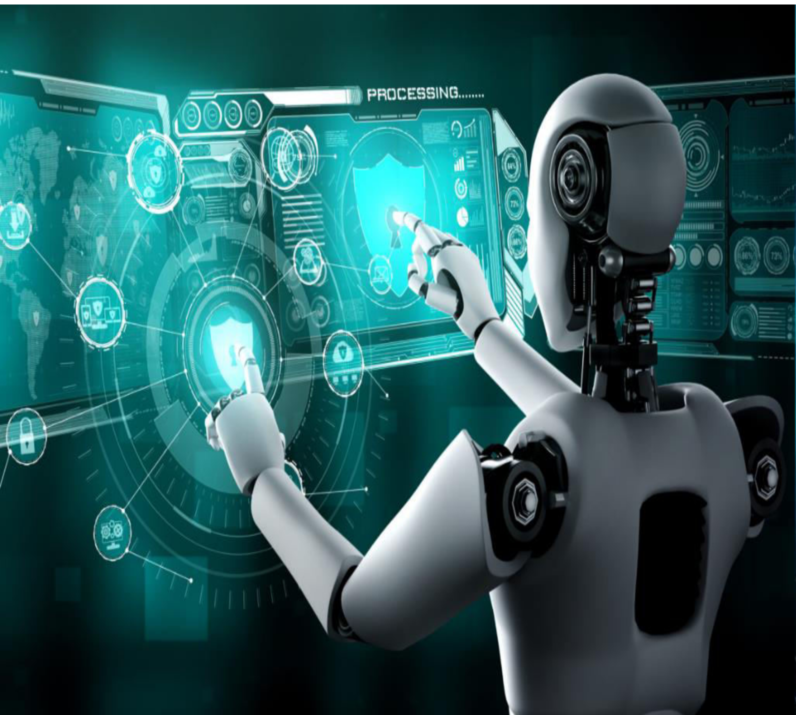

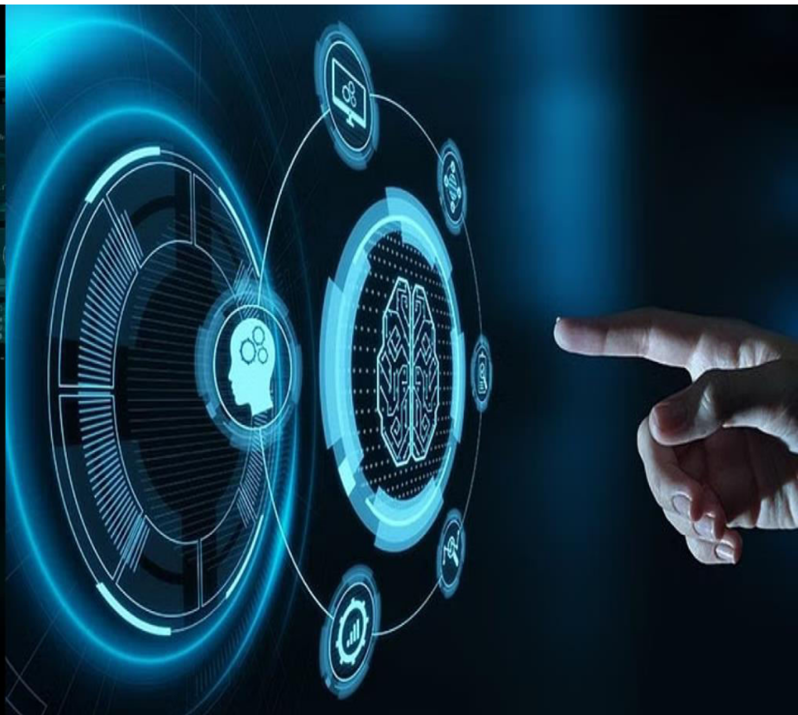

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Indian Currency Classification using Transfer Learning with Attention Mechanism for Blind People

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ABSTRACT: Indian currency classification refers to segmenting the Indian currency notes and subsequently giving it a class based on their value using computer vision. Traditional modelling approaches, including CNN, tend to fail on issues, which include; differences in lighting at the time of image capture, different backgrounds and similarities between the denominations. Often these models do not possess a mechanism to look at a specific detail within an image hence achieving low accuracy. It is particularly for visually impaired individuals who mostly face challenges in accurately finding banknotes due to their trust in tactile or external assistance. This study seeks to fill these gaps by employing a deep learning approach by transfer learning with the Xception model, which incorporates an attention mechanism. In turn, we use transfer learning to incorporate weights from a large dataset into the model, which helps the model to generalize and identify features on currency notes. By following this principle, the attention mechanism can enable the model to amplify concentration on observation areas such as security features, and small details which are essential for classification. The proposed approach has introduced a high accuracy of 91%, which can help to overcome all typical CNN disadvantages and create an effective solution for currency classification in real conditions. Nevertheless, the study also enhances a simple Flask-developed web application. This study introduces a smart system that uses advanced technology to help blind individuals recognize Indian currency notes easily and independently.

KEYWORDS: Indian Currency Classification, Currency Recognition, Convolutional Neural Networks (CNN), Xception Model, Transfer Learning, Attention Mechanism, Deep Learning

I. INTRODUCTION

Currency classification is a basic activity in the field of computer vision and artificial intelligence which aims at designing the ways to identify and sort currency notes depending on their visual characteristics [1]. In this process, it involves image analysis of the currency notes to determine its different denominations as well as to capture fake bills in large scale automation of banknotes mainly in the banking, retail, and financial sectors.

People who are blind and visually impaired struggle daily to recognize currency notes especially during financial transactions when currency identification remains essential [2]. Visually impaired individuals must frequently fall back on touch-based characteristics or borrow help from others because these options often lead to logistics problems or bad reading experiences or compromised personal privacy [3]. The written clues such as braille markings or embossed designs on currency notes remain inadequate [4] because they degrade or conflict with printed design variables over time. New technological solutions must emerge right now to develop systems which let blind people identify their currency with independence and precision. Computer vision and deep learning innovations have led to the development of automated currency classification systems which now represent an effective solution to track currency identification properly. Such technologies enable systems to process captured image data which results in real-time currency identification protocols delivered through audio and accessible modulations. This study develops improved Indian banknote currency classification by implementing an Xception model combined with an Attention Mechanism which increases accuracy and reliability. This study targets blind users with all required features to enable quick identification using real-time capabilities. The suggested system focuses on detecting distinctive currency characteristics because it offers performance stability that exceeds traditional identification techniques which cannot perform well under different lighting or background conditions. The solution deals with currency classification technical challenges while creating better accessibility for blind individuals and their goal of financial independence. This study advances visual impairment quality of life through an accessible practical application which enhances both money handling simplicity and security.

Figure 1 is showing labelled specimen of Indian 2000 currency note which is showing some key security features like watermark, micro lettering and all

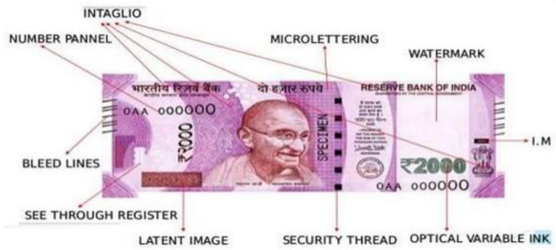

Figure 1: Specimen Copy of Rs 2000 Currency note by [5]

II. RELATED WORK

There are some previous works which will show work which is done in different currency classification. First study provided in [1] which focuses on identifying the genuineness of money using two unique machine learning algorithms – K-Nearest Neighbor (KNN) and Convolutional Neural Networks (CNN) due to the growth in cases of fake currency and the improvement in quality printing technologies. This paper aims at identifying fake and real money with complete digital imagery under controlled circumstances in terms of exposure rate, capture angles and image resolution. For KNN the accuracy was at a 87.75% and for CNN; the accuracy score was slightly higher at 96.67%. However, these encouraging results underscore some significance on improving the results through utilizing better preprocessing on the obtained dataset. Limitations include difficulties that may be encountered when adaptation the theory in real life situations when there are differences in lighting, angle, or image resolution. It is possible in future studies to work on expanding the diversity of used data and improving the pre-processing and optimization of the model.

The study [2] aims at improving the reliability of the cryptocurrencies' value forecasting by comparing the rf technique's innovation to the k-nearest neighbor (knn) technique. This research applied machine learning approaches to design such algorithms and as for the assessment of pretest power analysis, its parameters included an alpha of 0.05 and a beta of 0.85 The P-value in this study was less than 0.05 levels of statistical significance. It was concluded that the RF algorithm outperformed the other algorithms with the highest accuracy of prediction at 87.7330% for the RF as compared to KNN with accuracy of 72.1250% and the differences were subsequently validated as statistically significant through an independent sample t-test at t = 0.760. Still, the study shows how the RF algorithm can help enhance the cryptocurrency price prediction; yet, it should be recalled how the analysis is stagnant in a wide extent, such as fixed setup parameters and the sample set size are limited. More future studies may include the use of other datasets to test the proposed methods and analyze more model improvements in greater detail for further confirmation and generalization.

In this research work [3], an evaluation of these neural networks with convolutional parts as safer alternatives to the conventional multilayer perceptron for the trend classification of cryptocurrency exchange rates based on high-frequency technical analysis is conducted. The study investigates four kinds of networks: CNN, CNN-LSTM, MLP, and RBF, based on their capability of forecasting whether the value of six cryptocurrencies (BTC, DASH, ETH, LTC, XMR, XRP) will rise against USD within a minute. In this case, using eighteen technical indicators based on one minute exchange rate for a year, the authors discovered that all the series had a level of predictability using the indicators. The results also reveal that using Hybrid CNN-LSTM networks for predication leads to better accuracy in all the cases than CNN or LSTM alone, CNN achieved remarkable accuracy for Bitcoin, Ether, Litecoin. As with many technical studies, there is the problem of data gap, although this study used high-frequency data, it failed to account for the effects of news events and other macro factors in the cryptocurrency market. Here, future studies might examine how to incorporate such external variables to raise accuracy.

This study which is given by [4] who discusses an important topic of detecting counterfeit Indian currency notes due to the latest technological developments in colour printing which presents a real challenge to the racketeers in preparing

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their differently designed fake notes. The research puts forward a three-layer model Deep Convolutional Neural Network (Deep ConvNet) to detect forgery in currency notes with an accuracy of 96.6%. This model has deep learning to assess currency underlying features that separates real from a fake note. On the same note the approach shows high accuracy, though the approach relies heavily on high quality image data and well controlled environment tests and could therefore be less useful in practice where images may be low quality or have since been tarnished. Such variations could be investigated in future work for improving the model's resistance towards such changes and using more actual-world datasets for training the model.

Another study given by [5] for extending their helping hand towards about approximately 12 million visually impaired persons in India for identification of currency note/notes for web/mobile using novel lightweight Convolution Neural Network (CNN) model. The model is capable of identifying Indian currency notes and is designed to both text as well as to speech out its results, which makes it more advantageous and easier to use. To train, validate and test the given model, a new dataset containing Indian currency notes was generated. As this was created employing TensorFlow, the hyperparameters were tuned for the best results and benchmarked with six other popular CNN architectures using transfer learning. The findings also show that the proposed model is better than the other models regarding the training and the testing accuracies which make the model efficient and realistic. However, limitations include: the model relies on a controlled set, the effect of worn out notes may not have been well captured, the model may not capture variations in lighting conditions. Using a broader dataset could be extrapolated for future studies to supplement the current model and improve its quality.

This paper [6] aims to discuss the problem of identifying sovereign debt and currency crisis, which are crucial for the stability of the international economy and financing. The research presents new models for predicting such crises based on the utilization of sophisticated computational methods and improve predictive capability compared to statistical models. To increase generalizability, the models' samples are amassed from a global pool, encompassing Africa, the Middle East, Latin America, Asia, Europe and elsewhere. Among these methods, the research conclude that the four methods of new generation are the most accurate and best to predict sovereign debt crisis, and the six methods including the deep learning neural decision trees, extreme gradient boosting, the random forests, and deep belief networks, the best for currency crisis forecasting. The findings suggest that computational methodologies are more accurate at enhancing the precision of predictions that can underpin macroeconomic policy and therefore improve the stability of countries' economies.

This study [7] aims at solving a very significant problem of differentiating between real and fake banknotes especially during processes such as demonetization where counterfeit notes are usually in circulation. The research proposes an automated system for detecting counterfeit currency using six supervised machine learning algorithms: SVM, Random Forest, Logistics Regression, Naïve Bayes, Decision Tree and KNN. The data set selected for the study is available in the UCI Machine Learning Repository and the performance of the constructed models is measured by performance metrics like Precision, Accuracy, Recall, MCC and F1-Score. The algorithms are tested on three different train-test ratios: 80:20, 70:30, 60:40, etc., and some models scored the exact possibility of being absolutely correct for some ratio.

This study [8] propose a novel model comprises two longest and most influential neural networks: Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) for predicting the closing price of FOREX currencies in the future. The model to be suited to the challenge of predicting in the FOREX market is an ideal model since this is a market with very many fluctuations. The first layer of the proposed model is the GRU layer with 20 neurons in the hidden layer, while the second layer is LSTM with 256 neurons in the hidden layer. The model was backtested on four major pairs: EUR/USD, GBP/USD, USD/CAD, USD/CHF at the 10-minute and 30-minute intervals from January 1, 2017, to June 30, 2020. The results were assessed using the mean square error, root mean square error, mean absolute error and R2 coefficient. For the given 10-minute timeframe, our hybrid GRU-LSTM model generates better results compared to standalone GRU, standalone LSTM and SMA- based statistical model, and for the 30-minute timeframe, it gives the best results for GBP/USD and USD/CAD pairs.

There is a study which has been proposed a camera phone-based money recognition system to help the visually impaired to recognize the currency notes; this examines the problem of recognizing money because the notes are of similar size and are also felt in a tactfully manner given by [9]. The system uses CNN and LSTM for the processing of

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each frame that has been detected by the camera as it moves closer to the note and the output is an audio message regarding the value of the currency. The accuracy of the model ranges to 92.55%, and thus the model is fast even when used in real environments. However, the approach may have limitations concerning the environment conditions like lighting conditions, camera quality, and the damage to the notes, and so on which affect the result of the system. There are prospects for further research on the strengthening of the model's stability to these real-world deviations and for expanding the range of the possibilities of the model for working with different currencies and their denominations.

Finally, in [10], the problem of identifying currency notes by the visually impaired when in a class to be assisted by other people is mitigated thus leaving them at the mercy of other people. For still more independence, the study recommends a deep learning model that can identify Indian currencies using pictures of the notes. A number of deep learning models were experimented and all of them had maximum accuracy level of 80%. The model will help the visually impaired people to be more independent to identify currency notes by themselves. The drawback of the study is that the variability of the lighting condition, image quality as well as the usage of currency note might vary significantly and this may affect the generality of the model under investigation in real life settings.

III. METHODOLOGY

This section will provide data preprocessing and feature selection section of this study.

A. Dataset Description

The dataset comprises 1,786 images of Indian currency notes spanning all seven denominations: Available denominations include ₹10, ₹20, ₹50, ₹100, ₹200, ₹500; as well as ₹2000. It contains them for the ₹10, ₹20, ₹50, and ₹100 notes, which show current changes of the design made by the Government of India. All them images belong to a real-world dataset, which was obtained using the mobile phone camera and under different conditions, including different backgrounds, lighting conditions and camera positions to capture a diverse dataset. The distribution of images across denominations is as follows: ₹10 for 215 images, ₹20 for 331 images, ₹50 for 272 images, ₹100 for 301 images, ₹200 for 205 images, ₹500 for 223 images and ₹2000 for 239 images. No further transformation to the features of the captured images was performed to ensure that the recorded visuals remain as natural as possible. From the provided dataset, one is benefited solving the problem of currency classification with machine learning methods, the difficulties of which are shown as the class imbalance and the variability of image conditions.

B. Data Preprocessing

In the data preprocessing step of the improved currency identification project, several main approaches were taken to preprocess the data: the dataset containing images of Indian currency notes for model training. First, the images were named to place proper class values that belong to the given image according to their respective denominations. All the images used in the study were preprocessed and resized to a standardized image dimension using OpenCV. This step was very useful since images in the set varies in sizes and orientations apart from being captured in different lighting conditions.

Then the categorical labels, which stands for the currency notes, were changed into numerical format using LabelBinarizer class. This encoding mapped all those denominations into an array of binary, a format that could feed into the model. These transformed labels were then serialized and dump to pickle file format using python's pickle module and stored for further usage. This made sure that during both the model evaluation and the model deployment phase, the label transformation previously applied is used. The total count of unique individual classes, the denominations in this case was obtained using the length of the classes_ attribute of the LabelBinarizer. These preprocessing techniques helped in preparing the useful information in the data set with favorable labels to feed into the next step in training the neural network to make those classification on the currency notes.

C. Data Balancing

Since the currency classification dataset had an imbalance in the number of data samples per denomination, Synthetic Minority Oversampling Technique (SMOTE) was used for oversampling of the minorities. First, the image data was restructured in the form of a matrix consisting of two dimensions where every image was transformed into a vector and all the pixels forming that certain image were placed one after the other. This was done with a view of making the data amenable to the SMOTE algorithm, which only works on tabular data. The actual process of SMOTE entailed first identifying the minority classes in the given set of data and then creating additional synthetic samples for the given

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limited classes through an interpolation process. This would make each denomination balanced for the models, to avoid situations where when training the model, some classes are favoured over others because of the number of samples available for each class. Subsequent to oversampling, the reshaped data was again converted back to 3 dimensional image data so that it would maintain its pixel dimensions and channels to that provide input to Convolutional Neural Network. This approach was beneficial in strengthening the heterogeneity of the feature pool and increasing the potential of training data, allowing the model to learn representative features, with reference to different forms of currency.

D. Data Splitting

The dataset is been divided and then analyzed into training, testing and validation data to ensure that the data has been split effectively for purpose of evaluation. Initially, the dataset is split into two parts: 90% for training and validation and 10% for testing. At 70% for training 20% for validation and 10% for testing. This is done with help of using the train_test_split method as assuring that the test set should represent the total data set and should include the different currency denominations properly. The remaining 90% is split comprises 70% for train and 20% for validation in the training process employ another split. The stratification process is also applied after the completion of the second split to make sure that all of the subsets maintain the complete proportional distribution of all of the currency notes classes to avoid sample bias in the training-validation set. As highlighted earlier, stratification is even more important in this project because the data is imbalanced meaning that, for instance, the category of 20-rupee notes has many samples than 200-rupee notes. This careful division results in a 70:To train, validate and test the model an 10:20 split of the data is done so that the available data can be used efficiently to learn from and for the evaluation of the model. The last third of the data is only used once to evaluate the final model and therefore offers a completely unbiased estimate of the model's performance on unseen data.

The horizontal bar chart in figure 2 seems to depicts a dataset's class distribution before applying SMOTE (Synthetic Minority Over-sampling Technique). This passes class labels which are 100, 20, 500, 200, 2000, 50, and 10 on the x-axis and count/frequency of instances in each class on the y-axis. Clearly, the samples are unevenly split; class "20" has the most at around 325 samples, while class "100" has slightly fewer than that with about 300 samples. The fourth and second most frequent are classes "50" and "2000" manifesting approximately 270 and 240 instances respectively The last two classes "500" and "200" are less frequent manifesting nearly 220 and 205 instances respectively. The frequency of use of the class called "10" turns out to be the lowest with about 210. This is likely so because of the given skewed class distribution of the data shown above, and since there are instances ML algorithms work better when class distributions are balanced, SMOTE has to be applied to balance the classes. The great disparity in frequency distribution of different classes has the potential of leading to other classes being overemphasised in predicting models if not handled.

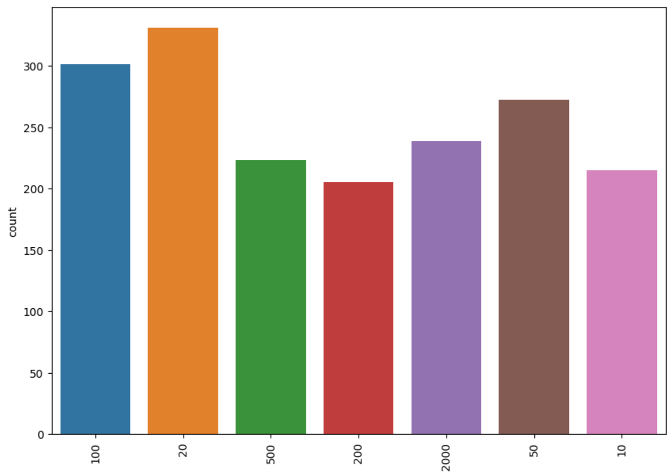

Figure 2: "Class Distribution Before SMOTE: Initial Dataset Imbalance"

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This bar chart in figure 3 shows the new distribution of the dataset after balanced by using SMOTE since the previous figure highlighted an imbalance in the class. The x-axis remains the same with the class labels (100, 20, 500, 200, 2000, 50, and 10) while the y-axis shows the count of instances and looks like the following figure which is a totally balanced data set with 325 instances for each class. The combination of synthetic samples by SMOTE algorithm has been achieved with consideration of the minority classes, thereby, has made them equal to the number of samples in the formerly dominant class.

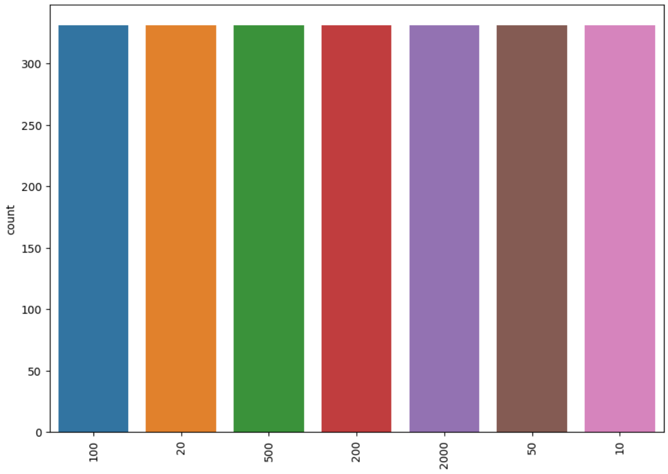

Figure 3: "Balanced Class Distribution After Applying SMOTE"

E. Exploratory Data Analysis

This figure 4 illustrates a faceted subplot of the images of seven Indian currency notes including 10, 100, 2000, 50, 500 notes after SMOTE and are carrying out an exploratory data analysis (EDA) on the image dataset. All subplots display images in grayscale or colours to show the variability of currency notes by illuminating images captured from various orientation and lighting conditions with the X and Y axes scales denoting pixel dimensions to 4000 units. The visualization further illustrates the types of image samples obtained for each denomination class after applying SMOTE for balancing the dataset and to get an idea about the visualization of the images and the quality of the new images created using SMOTE technique.

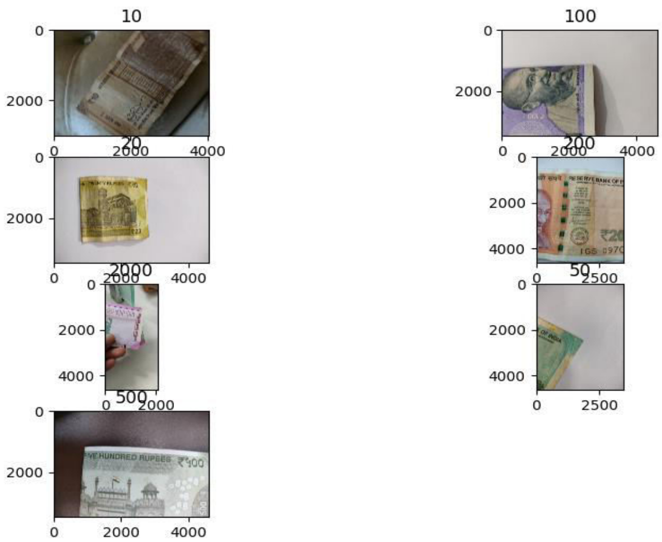

Figure 4: "Sample Images of Indian Currency Notes Across Denominations After SMOTE"

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Figure 5 is showing proposed workflow diagram of this study which starts from dataset collection to web based flask web application.

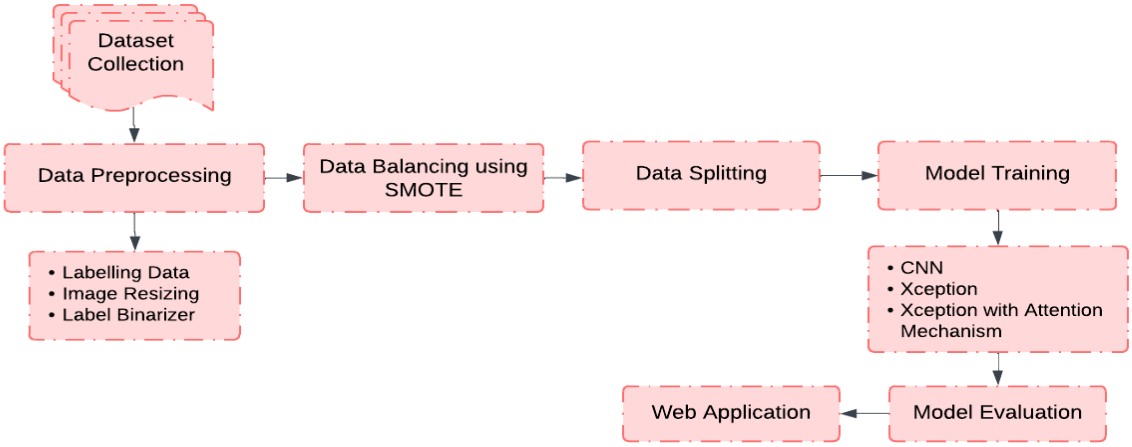

Figure 5: Proposed Workflow Diagram

IV. EVALUATION RESULT

A. Classification Performance of CNN Model

Figure 6 shows the value of sensitivity and specificity of each class (0-6) in the currency classification in the CNN model. The table reveals very high sensitivity scores of every class; class 0 has 0.980488; class 2 has 0.984375; and class 5 has 0.979275, showing good number of true positive. However, the specificity scores are comparatively lower in several classes such as class 0 (0.296296), class 2 (0.300000) and class 5 (0.256410), which indicating that the model may not so good in identifying true negatives.

	class	sensitivity	specificity
0	0	0.980488	0.296296
1	1	0.787879	0.882353
2	2	0.984375	0.300000
3	3	0.919598	0.303030
4	4	0.905000	0.906250
5	5	0.979275	0.256410
6	6	0.843902	0.481481

Figure 6: Sensitivity and Specificity of CNN Model

Figure 7 below illustrates a confusion matrix of CNN, meaning higher numbers depict predictions of CNN, while lighter shades depict fewer predictions. The y-axis: the actual classes ranging between 0 to 6 and the x-axis: the predicted classes ranging between 0 and 6 as shown in the figure. The diagonal elements show correct predictions, with notably strong performance in several classes: Among these, class 1 has the largest number of correct predictions, 30, followed by class 4 which has 29 correct predictions as identified by the darkest shades of blue.

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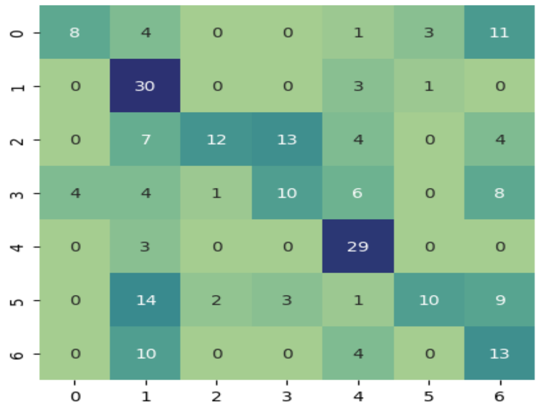

Figure 7: "Confusion Matrix for CNN Model Performance in Currency Classification"

B. Classification Performance of the Xception Model

The sensitivity (true positive rate) and specificity (true negative rate) features of the Xception model are depicted in Fig 8 for 7 classes (0-6). In classes 0, 2, and 4, there is perfect sensitivity, equal to 1.000000, so the model is perfect at detecting true positives in these classes. The specificity coefficients are somewhat different and fluctuating, starting from 0.185185 for Class 0 and reaching to 1,000000 for Class 6, while the most of classes were with specificity of 0.70 and above.

	class	sensitivity	specificity
0	0	1.000000	0.185185
1	1	0.984848	0.735294
2	2	1.000000	0.600000
3	3	0.904523	0.909091
4	4	1.000000	0.968750
5	5	0.917098	0.948718
6	6	0.926829	1.000000

Figure 8: Sensitivity and Specificity of the Xception Model

Figure 9 presented a confusion matrix which showed diagonality coefficients above 95, meaning that the survey retained very high commendations on most denominations' classification techniques.

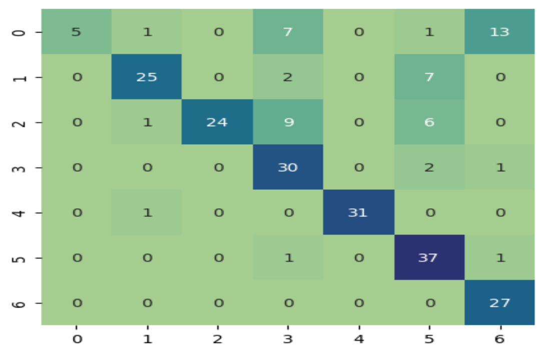

Figure 9: "Confusion Matrix for Xception Model Performance in Currency Classification"

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C. Classification Performance of EFFICIENTNET-B2 Model

Similar to the previous model, Figure 10 shows the sensitivity and specificity of the second proposed model: Xception with the attention mechanism. The model reaches 1.000000 on classes 0 and 1, and fluctuates slightly under 0.95 for all other classes but retains the perfect sensitivity for classes 0 and 1.

	class	sensitivity	specificity
0	0	1.000000	0.925926
1	1	1.000000	0.617647
2	2	0.994792	1.000000
3	3	0.994975	1.000000
4	4	0.995000	0.906250
5	5	0.953368	0.948718
6	6	0.956098	0.962963

Figure 10: Sensitivity and Specificity of the Xception with Attention Mechanism Model

Figure 11 illustrates the confusion matrix of the Xception model enhanced with an attention mechanism to classify Indian currencies denomination.

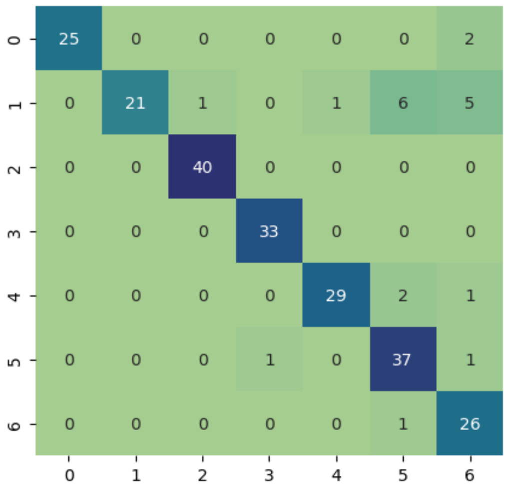

Figure 11: "Confusion Matrix for Xception Model with Attention Mechanism in Currency Classification"

The table 1 compares the accuracy of all three models which is been used for currency classification which includes CNN, the Xception model and the Xception model enhanced with an attention mechanism.

Table 1: Model Accuracy Comparison for Currency Classification

Model	Accuracy (%)
CNN	48
Xception	77
Xception with Attention Mechanism	91

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V. CONCLUSION & FUTURE SCOPE

This study presents an advanced solution for the classification of Indian currency notes using deep learning techniques. By leveraging transfer learning with the Xception model and enhancing it with an attention mechanism, the proposed approach achieves a significant improvement in accuracy, reaching 91% compared to the 48% accuracy of a basic CNN model. The attention mechanism enables the model to focus on critical regions of the currency notes, addressing challenges such as varying lighting conditions, diverse backgrounds, and similar features across denominations. The results demonstrate the effectiveness of modern deep learning techniques in overcoming the limitations of traditional models in currency classification. Moreover, the integration of a user-friendly web application using Flask allows for real-time currency identification, providing practical value to financial and retail sectors.

Future work can explore several avenues to further enhance the system's performance and usability. One potential direction is the inclusion of image augmentation techniques to artificially expand the dataset, improving the model's generalization ability. Additionally, exploring other advanced architectures, such as the EfficientNet or Transformer models, could lead to further improvements in classification accuracy. The system can also be expanded to handle currency notes from different countries, making it more versatile in international applications. Finally, future studies could focus on reducing model size and computational requirements to make the system more efficient for deployment on edge devices.

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