Accurate Biometric Palm Print Recognition Using ResNet50 algorithm Over X Gradient Boosting Algorithm

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ABSTRACT: The aim of this research is to enhance the accuracy of biometric palm print identification by using the Novel ResNet50 Algorithm as compared to the X Gradient Boosting. Materials and Methods: In this study, the ResNet50 and X Gradient Boosting algorithms were compared using a sample size of 10 for each algorithm, resulting in a total sample size of 20. The comparison was carried out with a G Power of 0.8 and a confidence interval (CI) of 95% to ensure statistical significance. For this study the Birjand University Mobile Palmprint Database (BMPD) dataset was collected from the Kaggle repository, which includes a total of 1640 images containing both left and right-hand palmprints. Result: According to the results, the ResNet50 algorithm achieved a higher accuracy rate (94.7%) compared to the X Gradient Boosting algorithm (92.4%) in identifying and measuring the images. The statistical analysis indicated a significant difference between the Novel ResNet50 algorithm and X Gradient Boosting, with a p-value of 0.003 (Independent sample T-test $p<0.05$). This suggests that the ResNet50 algorithm outperformed the X Gradient Boosting algorithm in this experiment. According to the study's findings, ResNet50 is more effective in accurately identifying biometric palm prints compared to X Gradient Boosting.

Keywords: Biometric, Fingerprint, Novel ResNet50, Palm Print, Technology, XGradient Boosting.

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INTRODUCTION

Predicting the accuracy of palm print recognition as a percentage is the aim of this study. Therefore, "physiological" and/or "behavioral" are the two main types of biometrics (Nanni and Brahnam 2021) The physiological category encompasses the physical characteristics of humans, including veins, eyes, hands, and palm prints. The behavioral category comprises a person's movements, including hand gestures, speaking patterns, signatures, etc (Rozema 2023). The assessment of these characteristics aids in biometric system authentication. This study presents various hand biometric characteristics that can be used to identify a person (Neware 2020). The goal of this study is to offer a multimodal biometric technology that makes use of several biometric features, including palm, finger, and finger knuckle prints (FKP) (Arya and Bhadoria 2019). It is suggested to create scores for each modality independently and then combine them at the decision level using the Convolution Neural Network and Softmax classifier.
According to the current investigation, there were 118 papers in IEEE Explorer and 1200 articles in Google Scholar. Three physiological features: fingerprints, palm prints, and hand veins are used in this study's multimodal biometry to identify the person. In the pre-processing stage (Jaswal, Kanhangad, and Ramachandra 2021) the input fingerprint, palm print, and hand vein photos are first cleaned up to remove any extraneous areas, noise, and blur effects. This extracts the features from these three modalities (Vinothkanna and Wahi 2017). One of the most important and research-demanding fields is automatic identity verification technology. This work introduces an identity verification technique based on the median robust extended local binary pattern (MRELBP) (Dobbie 2020). The MRELBP technique is used in this system to extract features from the images after normalizing them and extracting the ROI from the microscopic input image. A new method of identity verification based on median robust extended local binary pattern (MRELBP) is introduced in this study (Sinno 2018) .
According to the study gap found in the existing literature survey, palm print recognition has lower accuracy, poorer picture quality, and necessitates a longer process in order to obtain accurate accuracy values. The ResNet50 method is suggested as a way to attain these outcomes, which gives more accuracy while consuming less time and using a higher output efficiency than other algorithms. These algorithms' evaluation and results largely depend on precision, which requires more time. Hence, this research seeks to recognize palm prints using Novel ResNet50 to improve accuracy.

MATERIALS AND METHODS

This study was conducted at Saveetha School of Engineering, Department of Computer Science. Two study groups were considered for the experiment (Nasir et al. 2022). The project's goal was to encourage the development of a machine-learning system for palm print recognition. where each group consists of 10 samples and 20 samples in total. The sample size was calculated using alpha value of 0.05, and G-power value of 80%, and with CI of 95% (Genovese, Piuri, and Scotti 2014). Two algorithms, Novel ResNet50, and X Gradient Boosting are implemented in MatLab software that is used for the identification of palm prints. The statistical analysis for our study was done using IBM SPSS version 26. The palm print image has been taken as data for the execution
The Windows 10 operating system served as the platform for accessing machine learning. MATLAB software is used to plan and implement the suggested work. The hardware configuration included an Intel Core i3 processor and 4 GB of RAM. Birjand University

Mobile Palmprint Database (BMPD) Dataset (Kondeková et al. 2020) for the identification of biometric palm prints are taken from kaggle.com which was stored in .csv format. Independent T-test analysis is carried out to calculate the accuracy of both methods. The system type that was employed was 64-bit. The MatLab software is utilized for implementation. In terms of code execution, the image set is being worked on behind the scenes in order to complete an output process for accuracy.

ResNet50

ResNet50 can be trained with a significantly deeper network than typical CNNs, allowing it to learn a more diversified range of features from the input image. This makes it ideally suited for picture classification problems where the interactions between the input and output classes might be complex and nonlinear. ResNet50 is frequently used as a foundation model for transfer learning on various image classification tasks. This enables academics and practitioners to use the features learned by ResNet50 on the ImageNet dataset and apply them to their unique applications, generally with minimum fine-tuning. Even with a large number of layers, ResNet50 is computationally efficient. This makes it ideally suited for use in real-world applications with limited computational resources.

Procedure

Input: Utilizing palm print biometrics for identification purposes(Accuracy).
The included data has been obtained from the image.
Output: Enhanced Accuracy.
Function: ResNet50 Algorithm

1. Import the data from the Dataset.
2. Assign the input as a source image by reading it.
3. Test the ResNet50 Value.
4. Assess the ResNet50 Value.
5. Utilizing the training data to create a precise prediction in Biometric Palm Print.
6. Conducting prediction analysis to improve Biometric Palm Print forecasting efficiency.

Presenting the accuracy outcome of ResNet50.

X Gradient Boosting

XGBoost (eXtreme Gradient Boosting) is an open-source software library for gradient-boosting trees. A machine learning technique called gradient boosting combines a number of weak models (typically decision trees) to create a powerful ensemble model. Gradient boosting is extended by XGBoost by incorporating a number of speed enhancements, including regularization, parallel processing, and cache-aware memory access. Additionally, it features several built-in routines for dealing with categorical variables, handling unbalanced classes, and handling missing values, making it a flexible tool for diverse types of data. Overall, the data science community uses XGBoost extensively because it is a very effective and efficient gradient-boosting library. Building machine learning models with it is beneficial for a range of applications due to its durability, scalability, and accuracy.

Procedure

1. Define the training data and labels.
2. The images should be resized to a fixed size and converted to grayscale.
3. Split the data into training and validation sets.
4. Extract features from the images using an appropriate method, such as local binary patterns or Gabor filters. This will result in a set of feature vectors for each image.
5. Train an XGBoost model using the feature vectors from the training set. Set the appropriate parameters, such as the number of trees, learning rate, and the maximum depth, based on the characteristics of the dataset.
6. Analyzing the prediction for efficient prediction in Biometric Palm Print.

Output: Improved Accuracy.

Statistical Analysis

Utilizing the IBM SPSS software for statistical analysis in our study. The independent variables were the image and dataset, and the dependent variable was the improvement of accuracy values. An independent t-test was performed as part of the analysis to compare the means of the two independent groups (Gupta and Sharma 2022).

RESULTS

The proposed X-gradient boosting and Novel ResNet50 were run at different times in MATLAB with a sample size of 20. Table 1 shows the predicted accuracy value of ResNet50 and X gradient boosting. These 10 data samples are used for each algorithm to calculate statistical values that can be used for comparison. From the results, it is observed that the mean accuracy of ResNet50 was 94.7% and the X gradient boosting was 92.4%.

Table 2 shows that Novel ResNet50 has a mean, standard deviation, and standard deviation error mean of 94.7430, 1.47529, and .46653, respectively. Similarly, the mean, standard deviation, and standard deviation error for X gradient boosting are 92.4820, 1.49726, and.47348 respectively. The mean value of ResNet50 is better when compared with X Gradient Boosting, with a standard deviation of 1.47529 and 1.49726, respectively.

ResNet50's accuracy percentage (94.7%) versus X Gradient Boosting (92.4%) suggests that ResNet50 is more accurate than X gradient boosting, and a simple mean bar graph in fig. 1 shows that ResNet50's standard deviation is slightly lower than X gradient boosting. Figure 1 shows X-Axis: ResNet50 Vs X Gradient Boosting and Y-Axis: Mean accuracy of detection with +/- 2SD.

The ResNet50 method looks to be more accurate than the X Gradient Boosting. In Table 3, It shows that there is a statistically significant difference between the Novel ResNet50 algorithm and X Gradient Boosting with a value of $p=0.003$ (Independent sample T-test $p<0.05$). An independent sample T-test was performed to assess the accuracy of the Novel ResNet50 algorithm and X Gradient Boosting algorithms, demonstrating that our interpretation is correct.

Table 1. Accuracy of ResNet50 and X Gradient Boosting

S.NO	ResNet50	X Gradient Boosting
1	92.76	90.28
2	92.98	90.69
3	93.48	91.37
4	93.78	91.53
5	94.48	92.28
6	94.98	92.98
7	95.67	93.23

8	95.88	93.48
9	96.64	94.31
10	96.78	94.67

Table 2. Group Statistical Analysis of ResNet50 and X Gradient Boosting. Mean, Standard Deviation and Standard Error Mean are obtained for 10 samples. ResNet50 has higher mean accuracy compared to X Gradient Boosting.

	Algorithm	**N**	**Mean**	**Std.Deviation**	**Std.Error Mean**
Accuracy	ResNet50	10	94.7430	1.47529	.46653
	X Gradient Boosting	10	92.4820	1.49726	.47348

Table 3. Independent Sample T-test: ResNet50 is significantly better than X Gradient Boosting. It shows that there is a statistically significant difference between the Novel ResNet50 algorithm and X Gradient Boosting with a value of p=0.003 (Independent sample T-test p<0.05).

		Levene's test for equality of variances		**T-test for equality means with 95% confidence interval**						
		f	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean difference**	**Std.Error difference**	**Lower**	**Upper**
Accuracy	**Equal variances assumed**	0.000	0.987	3.402	18	0.003	2.26001	0.66470	.86451	3.65749

	Equal Variances not assumed			3.402	17.996	0.003	2.26001	0.66470	.86449	3.65751

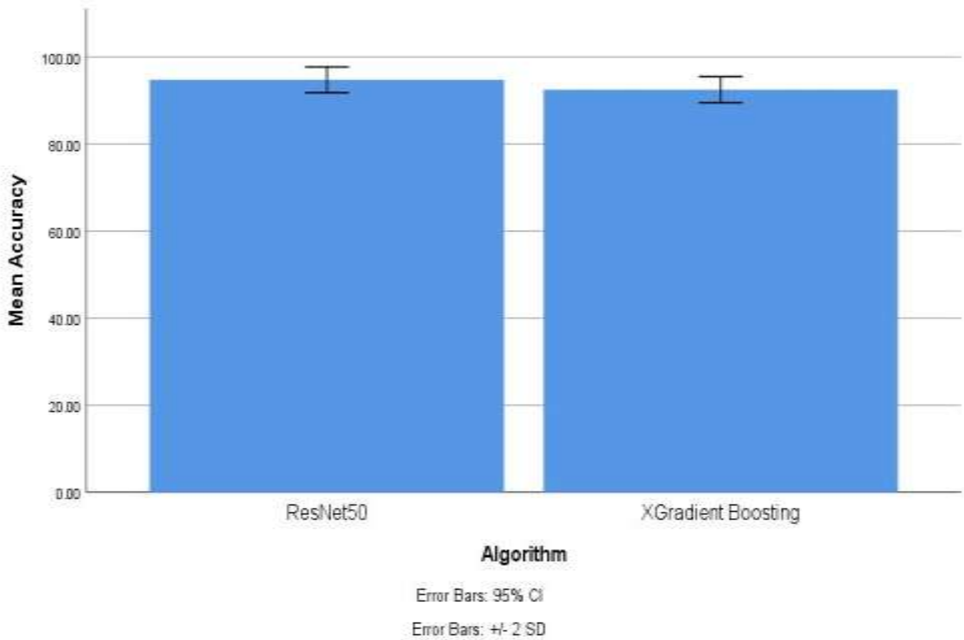

Fig. 1. Comparison of ResNet50 and X Gradient Boosting. Classifier in terms of mean accuracy and loss. The mean accuracy of ResNet50 is better than X Gradient Boosting. Classifier; Standard deviation of ResNet50 is slightly better than X Gradient Boosting. X-Axis: ResNet50 Vs X Gradient Boosting and Y-Axis: Mean accuracy of detection with +/- 2SD.

DISCUSSION

According to the findings, the objective of this study was to compare the accuracy of two algorithms, namely Novel ResNet50 and X gradient boosting, in identifying biometric palm prints. The findings indicate that Novel ResNet50 performed better with an accuracy rate of 94.7%, while X gradient boosting achieved an accuracy rate of 92.4%. The significance value for this research is found to be 0.003 which is lesser than 0.05 ($p<0.05$) after performing the Independent samples T-test analysis. Therefore, it can be concluded that Novel ResNet50 is a more effective algorithm than X gradient boosting for palm print identification.

The method may have many great applications because there is a growing need for more secure biometric procedures. This technology offers greater spatial resolution and imaging depth compared to current IR and ultrasound-based palm-vessel imaging approaches

(Rehman et al. 2022). Our method uses 3D structures instead of PAI-based fingerprint biometric technologies. It examines the scholarly literature as well as the most significant industrial uses of palmprint biometrics, (Kanchana and Balakrishnan 2015) including low-cost webcam-based systems (Genovese, Piuri, and Scotti 2014) and it is safer than 2D fingerprint mapping thanks to the addition of depth information. This study focuses on biometric recognition as a vital type of identification, one that is rapidly being employed in a wide range of applications enabled by advanced pattern recognition algorithms implemented via powerful lCT (Akinsowon and Alese 2013) and to further enhance the capability of detecting liveness, several wavelengths may one day be employed to assess hemoglobin oxygen saturation.

The palm prints image quality and lighting, which can have a negative effect on recognition accuracy, are the study's main limitations. Possibility of spoofing or fake palm prints, which can potentially deceive the recognition system. The accuracy and security of the system could be improved by adding extra sensors or features to help address these issues. Thermal imaging, for instance, could offer a more thorough analysis of the surface of the palm, resulting in a more durable system that could identify palm prints more quickly and accurately.

CONCLUSION

In this paper, two classification algorithms are used to identify biometric palm prints: Novel ResNet50 and X Gradient Boosting. ResNet50 (94.7%) looks to be more accurate than X-gradient boosting (92.4%). For recognizing biometric palm prints, the ResNet50 algorithm appears to perform much better than the X Gradient Boosting approach.

DECLARATIONS
Conflict of Interests
No conflict of interest in this manuscript.
Authors Contribution
Author HKK was involved in data collection, data analysis and manuscript writing. Author SAK was involved in conceptualization, data validation and critical reviews of manuscripts.
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