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Research Article

Interpretable Ensemble Models: A Feature Contribution Analysis with Explainable AI

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ABSTRACT

Ensemble learning offers improved predictive accuracy compared to its constituents but often lacks transparency in understanding the influence of individual learners. This work addresses this challenge by applying Explainable Artificial Intelligence (XAI) techniques to evaluate feature contributions within ensemble models. In this paper, an ensemble model, developed using stacking techniques, is used for the feature relevance analysis. This model is designed as a feature ensemble for yoga posture detection by combining three feature sets: keypoints, angles, and Hu moments. This analysis is performed with two explainable techniques, SHAP (SHapley Additive exPlanations) and the Permutations of feature importance method. The results highlight not only the important features but also reveal varying contribution patterns depending on the XAI technique used. Both of the methods put forward Hu moments as the most contributing feature. This investigation could promote the use of the underexplored feature, Hu moments, in further studies of posture recognition.

Keywords: Explainable AI, SHAP Analysis, Permutation Feature Importance Method, Ensemble methods, Yoga posture Recognition

INTRODUCTION

The automation of yoga pose identification has attracted considerable research interest with the advancement of Artificial Intelligence (AI) techniques. Ensemble learning has emerged as a highly effective strategy in machine learning due to its ability to combine predictions from multiple models and deliver superior performance over individual learners[1]. Although some studies have applied ensemble methods to posture recognition[2], [3], they primarily rely on image-based features, often lacking effective feature engineering. In addition, they have not sufficiently investigated how each base learner contributes to the final prediction. This research addresses that gap by applying the XAI technique on an ensemble model constructed with three well-defined feature sets. Building upon our prior work[4], which demonstrated the effectiveness of Hu moments in posture recognition, this study further investigates the contribution of Hu moments, a global shape descriptor, alongside the widely used local features, key points, and angles. The integration of explainable AI techniques helps overcome the black-box limitation of ensemble models, offering insights into the relevance of each feature set [5]. The primary objective of this work is to analyze and interpret feature contributions within ensemble models to enhance the transparency and performance of yoga posture classification. The main objectives of this work are

1. This work bridges the gap in the black box nature of the ensemble learning mechanism for yoga posture recognition by incorporating explainable AI techniques, specifically SHAP and Permutation Feature Importance.
2. This work equips the feature-based ensemble model to interpret and quantify the contribution of individual features within each feature set.

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3. This study highlights how different explainability methods complement each other in uncovering feature significance within ensemble models.
4. This study contributes to the goal of building trustworthy and explainable AI systems, particularly in the context of human posture or activity recognition tasks.
5. Unveiling the importance of the underexplored shape feature, Hu moments in activity recognition, specifically yoga pose detection.

METHODS

1. **Feature Extraction:** To comprehensively capture the structural, geometric, and shape-related aspects of yoga postures, three distinct feature sets were extracted from the same dataset: key points, angles, and Hu moments. Key points were obtained using the Mediapipe framework [6], which detects 33 body joints. Each joint includes four parameters—three-dimensional spatial coordinates (x, y, z) and a visibility score. These values were flattened into a feature vector of 132 dimensions for model input. Angle features were computed from the key points using an optimized angle calculation method to capture meaningful joint relationships while minimizing redundant computations. For Hu moments, the images were first segmented using DeepLab v3 to isolate human figures from the background. Hu moments consist of seven descriptors that collectively capture the global shape of the posture and are invariant to scale, rotation, and translation, providing complementary information to the more localized key points and angle features. Three Random Forest (RF) models were developed based on these feature sets to serve as base learners for the ensemble framework.
2. **Ensemble Model Design:** The three base learners, each trained on a distinct feature set, were merged into a stacking ensemble to combine the strengths of all feature categories. The meta learner is another ML model that takes the probability distribution of base learners and finds the best way to combine these distributions for optimum results[7]. In this work, Logistic Regression[LR] is used as the meta learner.
3. **Feature Relevance Analysis:** The primary objective of this paper is to understand the contribution of the feature set in the final prediction, while they complement each other during ensembling. For this, we applied two XAI methods, SHAP and Permutations, for feature importance. SHAP is a technique, derived from game theory, to explain the individual contribution of features in a final prediction[7]. It operates based on an additive feature attribution framework, where the prediction is expressed as a sum of contributions from each feature. The SHAP value for the i^{th} feature quantifies its marginal contribution by considering all possible combinations of feature subsets. Formally, the SHAP explanation model is represented using Equation (1):

$$g(z) = \phi_0 + \sum_{i=1}^{M} \phi_i z_i \qquad (1)$$

where: $g(z)$ is the explanation model. ϕ_i is the contribution of the i^{th} feature $\phi_i \in R$, 'm' is the size of the combined vector, which is represented as $z \in \{0,1\}^M$, where 1 indicates the presence of the feature and 0 indicates its absence.

The second explainability approach used in this study is **Permutation-based Feature Importance**, which evaluates feature relevance by randomly shuffling the values of a feature and observing the impact on model performance[8]. A feature is considered relevant if changing its values notably increases the model's error, indicating the model heavily relies on that feature for accurate predictions. This method aligns with the concept of **Model Class Reliance (MCR)** [9], which quantifies how much a model depends on a particular feature. This study identified the top ten most relevant features using this method for both XAI methods. Additionally, the relevance of each feature group was further analyzed and validated using both techniques.

RESULTS AND DISCUSSION

Experimental Settings : This study utilizes a subset of the publicly available Yoga-82 dataset[10], comprising 10 classes with approximately 300 images per class. All experiments were executed in a GPU environment using Google Colab.

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Results : Feature contribution analysis used two explainable AI methods: Permutation Feature Importance and SHAP. The feature importances derived from the Permutation method are summarized in Table 1. The SHAP-based visualization of feature relevance is illustrated in Figure 1. Additionally, Groupwise permutation importance for each feature category is presented in Table 2, while Figure 2 depicts the corresponding SHAP visualization.

Table 1 Feature Importance Identified using Permutation Feature Importance Method

Feature	Importance
139	0.0033
158	0.0024
140	0.0022
152	0.0017
73	0.0017
81	0.0017
161	0.0016
89	0.0016
125	0.0014
151	0.0014

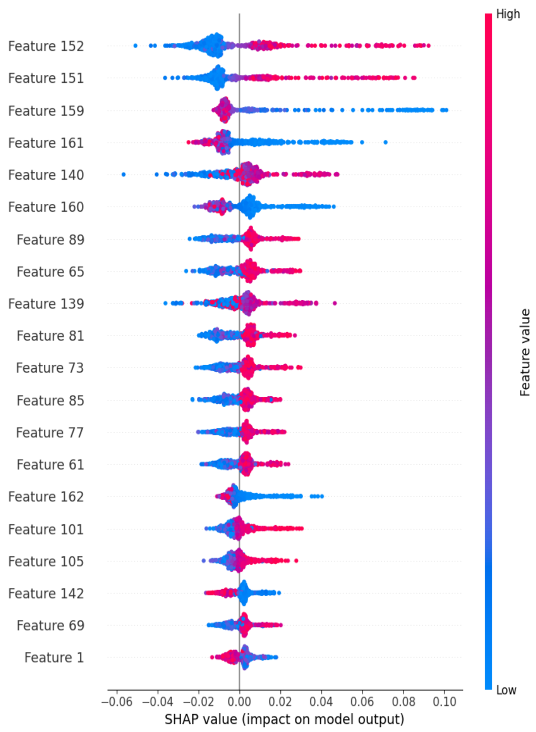

Figure 1 Visualization of important features extracted using SHAP analysis

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Table 2 Feature Importance Identified using Permutation Feature Importance Method

Feature Group	Importance
Key points	-0.0002
Angle	0.0003
Hu moments	0.0009

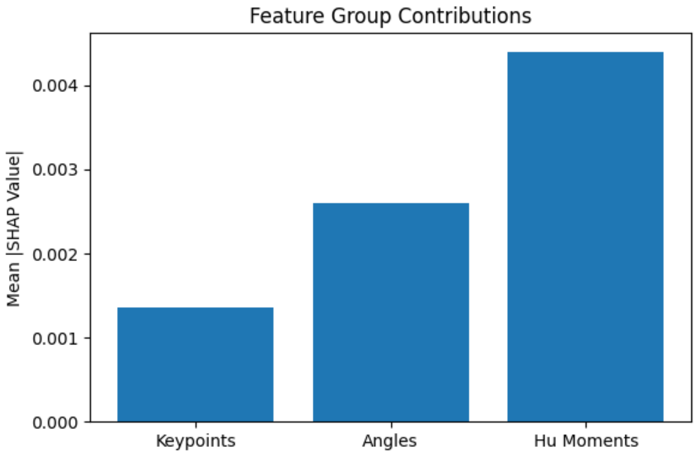

Figure 2 Visualization of Groupwise importance of features identified using SHAP analysis

Discussion : Both explainability methods consistently identified Hu moments as the most significant feature for yoga posture classification. Hu moments, composed of seven invariant descriptors, effectively capture global shape characteristics regardless of transformations such as rotation or scaling. To further understand the individual contribution of each Hu moment, a detailed SHAP analysis was conducted, with the results visualized in Figure 3.

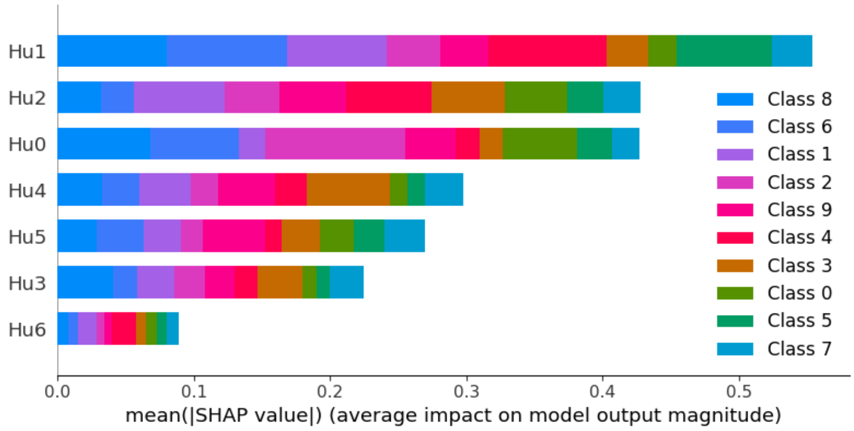

Figure 3 Visualization of the contribution of Hu moments' components identified using SHAP analysis

CONCLUSION

This study investigated the contribution of individual features in ensemble learning models using explainable AI techniques. An ensemble model was developed as a combination of key points, angles, and Hu moments using the stacking method. Feature importance was assessed using SHAP and Permutation Feature Importance, offering

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insight into each feature's impact on model predictions. The results consistently identified Hu moments as the most influential feature since they capture the global shape of the posture, providing a more comprehensive representation compared to the localized information from key points and angles. Furthermore, the comparative use of SHAP and Permutation methods validated the consistency of the results and demonstrated how different explainability techniques complement each other in revealing feature significance. Moreover, this work can be a milestone since it unveils the relevance of Hu moments in posture recognition.

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