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EWSMLFS: Explainable Weighted Stacked Ensemble Machine Learning with Recursive Feature Selection for Higgs Boson Particle Detection and Classification

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Abstract: This research paper addresses the critical task of detecting and classifying Higgs Boson Particles (HBP) in high-energy physics research. We propose an explainable weighted stacked ensemble Machine Learning (ML) approach with Recursive Feature Selection (RFS) to achieve accurate results while ensuring model interpretability. By leveraging ensemble learning, we combine multiple Base Models (BM) in a stacked ensemble framework, assigning weights based on their performances to enhance prediction accuracy. We use RFS to identify the most relevant features to improve interpretability, reducing dimensionality and helping with a clearer understanding of the underlying physical processes. Our experiments on the HBP measurements dataset show our approach outperforms baseline models while maintaining transparency. We evaluate our model using key metrics, including accuracy, precision, recall, and F1 score. We analyze the interpretability of the ensemble and identify the most important features contributing to the classification process. Our results indicate that the proposed approach strikes an optimal balance between accuracy and interpretability. The combination of weighted stacked ensembles and RFS provides valuable insights into the HBP detection process. Scientists can gain a deeper understanding of the underlying physical phenomena, enhancing the reliability and trustworthiness of the particle classification results.

Keywords: Higgs boson particle detection, machine learning, weighted stacked ensemble, recursive feature selection, interpretability, high-energy physics.

1. Introduction

The discovery of the HBP in 2012 at the Large Hadron Collider (LHC) marked a significant milestone in particle physics. The Higgs boson is a fundamental particle predicted by the Standard Model, the prevailing theory describing the elementary particles and their interactions. Its discovery confirmed the existence of the Higgs field, which is responsible for giving particles their mass [1,2]. HBP detection and classification are crucial tasks in high-energy physics research. Accurate identification and classification of these particles provide essential insights into the fundamental forces and particles that are the universe. Understanding the properties and behavior of the Higgs boson is crucial for unraveling the mysteries of the universe, such as the origin of mass, the nature of dark matter, and the unification of fundamental forces [3,4].

The detection and classification of HBP are challenging due to their rare occurrence and complex decay patterns. Experimental observations produce vast amounts of data, making manual analysis infeasible [5]. So ML techniques have become robust automated identification and classification tools. ML models can learn complex patterns and relationships from the data, enabling them to distinguish HBP from background noise accurately. These models use a wide range of features derived from the detector measurements, such as energy deposits, angles, and particle momenta, to make predictions. However, alongside accurate predictions, the interpretability of the models is imperative. Scientists must understand how and why a model arrives at a particular prediction to gain insights into the underlying physical processes. Interpretable models enhance scientific understanding, help with further discoveries, and ensure the reproducibility and trustworthiness of the results [4,6].
So developing ML approaches that provide accurate classification, and interpretability is crucial for HBP detection and classification. By combining the power of ML with Explainable Artificial Intelligence (XAI) techniques,

scientists can unravel the mysteries of particle physics and contribute to our fundamental understanding of the universe [7].

ML techniques [8] have become integral to particle physics research, enabling scientists to analyze vast experimental data and extract valuable insights. ML algorithms can learn complex patterns and relationships from the data, making them ideal for particle physics analysis. Several ML techniques are used in particle physics research, including supervised, unsupervised, and reinforcement learning. Supervised learning is the most common approach used for particle physics data analysis, where models are trained on labeled data to predict specific particles or phenomena accurately.

One of particle physics's most popular supervised learning techniques is the artificial neural network (ANN), a deep learning model. ANNs can learn complex non-linear relationships between features and have been used extensively for particle identification and classification tasks. Another popular ML technique used in particle physics research is Decision Tree (DT), which are simple models that recursively split the data into subsets based on the features' values. DTs are interpretable models used to classify particles and perform feature selection. Support vector machines (SVMs) are another supervised learning algorithm in particle physics research. SVMs are powerful models that can handle high-dimensional data and have been used for particle identification and classification tasks [9].

Unsupervised learning techniques [10], such as clustering and dimensionality reduction, are also used in particle physics research. Clustering algorithms group similar events or particles together, while dimensionality reduction techniques reduce the dimensionality of the data while preserving the relevant information. Finally, reinforcement learning, a type of ML where agents learn by interacting with an environment, has also been explored in particle physics research. Reinforcement learning has been used to optimize particle detectors' design and control particle beams. ML techniques have become essential in particle physics research, enabling scientists to analyze vast experimental data and extract valuable insights. These techniques can revolutionize our understanding of the universe, from supervised and unsupervised learning to reinforcement learning.

Model interpretability is crucial in scientific research because it allows researchers to understand the model's inner workings and gain insights into the underlying mechanisms that govern the data. In many scientific domains, such as medicine, biology, and physics, the interpretability of models is as important as their accuracy. First, interpretability gives researchers a better understanding of the data and the underlying phenomenon, enabling them to formulate new hypotheses and design more effective experiments. Often, a model's predictions are only as valuable as the insights it provides, and interpretability helps researchers to derive meaningful insights from the data.

Second, interpretability allows researchers to identify and correct errors or biases in the model. Not interpretable models may produce incorrect or misleading results, and it's challenging to locate and correct these errors without understanding how the model arrived at its predictions. Third, model interpretability is essential for ensuring the reproducibility and transparency of scientific research. Interpretable models enable researchers to explain how they arrived at their results and make sure others can reproduce their findings. Finally, model interpretability is crucial for building trust and credibility in scientific research. Researchers need to explain their models and results in a way understandable to others, including their peers, policymakers, and the general public. An interpretable model is more likely to be accepted and trusted than a black-box model, particularly in fields where high-stakes decisions are made based on the model's predictions.
The objectives of a project or study on HBP detection and classification using explainable weighted stacked ensemble ML with RFS could include:
1. To develop an accurate and interpretable ML model for detecting and classifying HBP.
2. To investigate the effectiveness of weighted stacked ensemble ML with RFS for HBP classification.
3. To evaluate the performance of the proposed model in terms of classification accuracy, precision, recall, F1 score, confusion matrix, and Area Under the ROC Curve (AUC)-ROC curve.
4. To compare the performance of the proposed model with other existing ML techniques for HBP detection and classification.
5. To provide insights into the features most relevant to classify HBP using feature selection techniques.
6. To examine the interpretability of the proposed model and provide insights into the underlying mechanisms that govern HBP detection and classification.

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2. Related Work

The literature in this compilation encompasses various research studies that focus on detecting and identifying HBP using ML techniques. These studies show the potential and effectiveness of ML methods in particle physics, particularly in Higgs boson classification, production mode disentangling, and decay mode identification.

Mourad Azhari et al. [11] propose using four ML methods (Logistic Regression (LR), DT, Random Forest (RF), and Gradient Boosted Tree (GBT)) in the Pyspark environment to solve the Higgs Boson Classification Problem. They compare the accuracy and AUC metrics for evaluation. Yi-Lun Chung et al. [12] show the use of ML to detect specific production modes of HBP produced via gluon-gluon fusion. Their approach combines jet substructure and event information with modern ML techniques to focus on particular production modes.

Murat Abdughani et al. [13] explore the potential of using message-passing neural networks (MPNN) to detect nonresonant Higgs pair production processes at the LHC. Their findings lead to an upper bound on the production cross-section of the Higgs boson pair. A. Mott et al. [14] apply quantum annealing to solve a ML optimization problem in Higgs-signal-versus-background classification. Their study shows that quantum and classical annealing-based classifiers perform comparably to state-of-the-art ML methods in particle physics.

Dimitri Bourilkov et al. [15] discusses using Boosted DTs in the CMS experiment to detect Higgs boson decays to dimuons, showcasing an increase in sensitivity equivalent to 50% more data. Rahool Kumar Barman et al. [16] explore using ML techniques to measure the Higgs-top CP phase in the ¯h channel at the high-luminosity LHC.

Alexander Lenz et al. [17] use ML and jet shapes to identify a boosted Higgs boson decaying into a charm pair. Alexandre Alves et al. [18] apply stacking ML classifiers to identify Higgs bosons at the LHC. Their findings show the competitive performance of stacked classifiers against deep neural networks. Vishal S. Ngairangbam et al. [19] shows deep learning techniques to detect invisibly decaying Higgs bosons, significantly improving the bound on the invisible branching ratio. Peter Sadowski et al. [20] trains artificial neural networks to detect the decay of the Higgs boson to tau leptons on a large dataset of simulated collision events, showing that deep neural network architectures are well-suited for this task.

Won Sang Cho et al. [21] discuss using deep neural networks and topological augmentation to improve the detection of di-Higgs production at the LHC. Roberto Santos et al. [22] present a systematic study of ML methods for detecting bar th in the h → bar b decay channel, with extreme GBTs and neural network models outperforming alternative methods. Benjamin Tannenwald et al. [23] studied different ML techniques for detecting Higgs boson pair production at the LHC, comparing boosted DTs, various neural network architectures, and semi-supervised algorithms.

These studies collectively show the potential of ML in detecting, classifying, and identifying HBP, providing valuable insights and advancements in particle physics. Adopting ML techniques can revolutionize particle physics experiments, leading to more accurate and efficient detection and identification of rare particles such as Higgs bosons.

3. Methodology

This section briefly discusses about the dataset used, feature selection using RFS, weighted ensemble stacking approach to design the proposed method.

3.1 Dataset Description

The HBP dataset used in the study is a collection of experimental measurements and observations related to detecting and classifying HBP. The dataset is derived from experiments conducted at the LHC or simulated based on theoretical models [11,24]. The dataset consists of features or variables that capture various characteristics and properties of the detected particles. These features are derived from measurements obtained from particle detectors, such as energy deposits, angles, momenta, and other relevant quantities. The specific features in the dataset may vary depending on the experiment or simulation setup. Each instance or sample in the dataset represents a detected event or particle, and the label associated with each instance indicates whether it corresponds to a HBP or belongs to the background noise. The label can be binary, where HBP are labeled as "1" and background noise as "0", or it can be multi-class, representing different particle types.

3.2 Feature selection using Recursive Feature Selection

RFE is a feature selection algorithm that recursively selects a subset of features by eliminating the least important features at each iteration. It uses a ML model to rank the importance of features and eliminates the least essential features until the desired number of features is reached [25].

Algorithm 1: Recursive Feature Elimination for Higgs Boson Particle Feature Selection

Input: Dataset X with n instances and m features: $X = \{x_1, x_2, \dots, x_n\}$
Target variable y: $y = \{y_1, y_2, \dots, y_n\}$, Number of desired features k
Output: Selected features: $selected\_features = \{f_1, f_2, \dots, f_k\}$

```
RecursiveFeatureSelection (X, y, k):
  if k ≥ m:
     Return all m features as selected_features
   else if k ≤ 0:
     Return an empty set as selected_features
  else:
     Initialize an empty set selected_features
  for i = 1 to m:
       Calculate the relevance score of features x_i regarding y
  Sort the features in descending order of their scores
  for i = 1 to k:
       Add the i − th feature from the sorted list to selected_features
 Return selected_features
```

3.3 Weighted Stacked Ensemble

The weighted stacked ensemble [11, 18, 26] with LR, RF, and DT are BM, and a meta-classifier LR can be represented mathematically:

Given a training dataset X and target variable y, the BM are trained independently:

- Logistic Regression: Let $f_1(X)$ be the LR model that learns a mapping from the input features X to the target variable y, such that $f_1(X) = P(y = 1|X)$. The LR model is trained by reducing the following loss function:

$$L(f_1(X), y) = -\left(y \log f_1(X) + (1 - y) \log\left(1 - f_1(X)\right)\right) \quad (1)$$

- Random Forest: Let $f_2(X)$be the RF model that learns a mapping from the input features X to the target variable y, such that $(f_2(X) = P(y = 1|X))$. The RF model is trained by building multiple DTs on bootstrapped samples of the training data and selecting the best subset of features for each tree. The final prediction is computed as the average prediction of all the trees.
- Decision Tree: Let $f_3(X)$ be the DT model that learns a mapping from the input features X to the target variable y, such that $f_3(X) = P(y = 1|X)$. The DT model is trained by recursively splitting the input space into smaller regions that reduce the impurity of the target variable.

The weighted ensemble is constructed:

- Weighted Averaging: Let w_1, w_2, and w_3 be the weights assigned to the LR, RF, and DT models, respectively. The weighted prediction of the ensemble is given by:

$$f(X) = w_1 \cdot f_1(X) + w_2 \cdot f_2(X) + w_3 \cdot f_3(X) \quad (2)$$

The weights are determined by reducing the validation error using a hold-out dataset.

- Meta-Classifier: The weighted predictions $f(X)$ from the BM are used as input features for a meta-classifier LR model, $g\left(f(X)\right)$, that learns to combine the base model predictions to generate the final ensemble prediction. The meta-classifier is trained on the same hold-out dataset as the weights.

$$g\left(f(X)\right) = P\left(y = 1\middle|f(X)\right) \quad (3)$$

The final ensemble prediction is obtained by evaluating the meta-classifier on the test dataset.

3.4 Interpretation of features through Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) techniques are essential for understanding complex ML models and providing insights into their decision-making processes. One powerful XAI method is the SHAP (SHapley Additive exPlanations) algorithm, which assigns each feature's contribution to the final prediction, promoting transparency and interpretability.

SHAP is based on cooperative game theory, specifically the Shapley value concept. The algorithm calculates the average contribution of each feature across all possible permutations of features. It determines how the addition of a specific feature affects the model's prediction compared to all possible combinations of features. The SHAP value ϕ_i for a given feature x_i can be formulated as:

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} \big(f(S \cup \{i\}) - f(S)\big) \quad (4)$$

Where, N is the set of all features, S is a subset of features excluding x_i, $f(S)$ is the model's prediction when using only the features in subset S, $f(S \cup \{i\})$ is the model's prediction when including feature x_i with the features in subset S, $|S|$ is the number of features in subset S.

By calculating the SHAP values for all features, we can gain insights into their individual impact on the model's predictions. Positive SHAP values indicate that a feature contributes positively to the prediction, while negative values suggest the opposite. Understanding these contributions allows us to interpret how the model is utilizing specific features to arrive at its decisions.

3.5 Proposed model

The proposed method for HBP classification and detection utilizes a Weighted Stacked Ensemble approach, as illustrated in Figure 1. The process involves several key steps aimed at achieving accurate and interpretable results. Firstly, the HBP dataset undergoes Data Preprocessing to clean and normalize the data. Feature engineering techniques may be applied to extract relevant features and reduce dimensionality, ensuring that the dataset is ready for model training.

Multiple BM are trained on the preprocessed dataset. These models can include LR, RF, DT, or other suitable algorithms. Each base model independently learns patterns and relationships in the data, capturing different aspects of the underlying physics.

The weighted stacked ensemble combines the predictions of these BM using weighted averaging. The weights assigned to each model are determined based on their performance on a validation set. This step ensures that the most effective models contribute more to the final prediction, improving the ensemble's overall accuracy and reliability. The meta-classifier, LR in this case, then takes the weighted predictions from the BM as input features and learns to generate the final ensemble prediction. It effectively combines the diverse knowledge of the BM to produce a robust and comprehensive classification outcome.

Once the weighted stacked ensemble model is trained, it undergoes evaluation using metrics such as accuracy, precision, recall, and F1 score. Fine-tuning of model hyperparameters may be performed to optimize its performance. Subsequently, the trained ensemble model is used for HBP classification and detection. Unseen data samples are passed through the model to predict their class labels, indicating whether they belong to the HBP category or not.

To further enhance interpretability, the SHAP algorithm is employed. SHAP assigns each feature's contribution to the final prediction, providing insights into how the model arrived at its decision. It explains the importance of features selected through RFS, offering valuable insights into the underlying physics involved in HBP detection and classification.

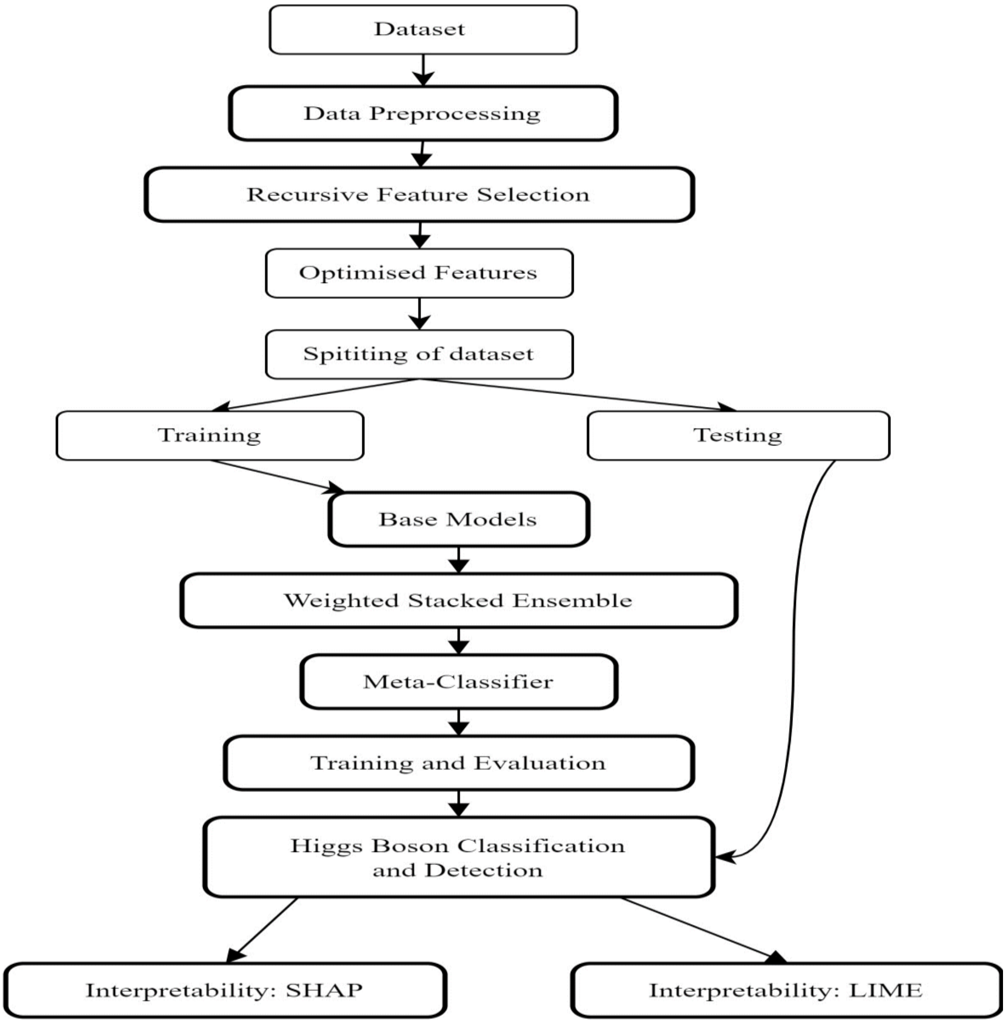

Fig. 1 Proposed Method for Explainable Higgs Bosson Detection and Classification

4. Experimental Results

4.1 Evaluation metrics used for performance assessment

The evaluation metrics commonly used for performance assessment in ML, along with their mathematical formulas:

1. Accuracy: Accuracy measures the proportion of correctly classified samples out of the total samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Where, TP: True Positive (correctly predicted positive samples), TN: True Negative (correctly predicted negative samples), FP: False Positive (incorrectly predicted positive samples), FN: False Negative (incorrectly predicted negative samples).

2. Precision: Precision measures the proportion of correctly predicted positive samples out of the total samples predicted as positive.

Precision $= \frac{TP}{TP+FP}$ (6)

3. Recall (Sensitivity or True Positive Rate): Recall measures the proportion of correctly predicted positive samples out of the total actual positive samples.

$$\text{Recall} = \frac{TP}{TP + FN} \ (7)$$

4. F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of the model's accuracy.

$$\text{F1 Score} = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \quad (8)$$

5. Area Under the ROC Curve (AUC-ROC): AUC-ROC is a performance metric that evaluates the classifier's ability to distinguish between positive and negative classes across different threshold settings. AUC-ROC ranges from 0 to 1, where a value closer to 1 indicates better performance.

4.1 Result and Discussion

Figure 2 shows the correlation matrix for the data. The matrix represents the pairwise correlation coefficients between different features of the dataset, ranging from -1 to 1. A correlation coefficient of 1 indicates a perfect positive correlation, 0 indicates no correlation, and -1 indicates a perfect negative correlation between two features. Looking at the matrix, we observe that some features have a strong positive correlation with each other, such as PRI_met_sumet and DER_sum_pt. Conversely, some features have a strong negative correlation, such as DER_mass_transverse_met_lep and DER_mass_MMC. It suggests that when one feature increases, the other decreases. Also, some features have a weak correlation close to zero, indicating that they are not strongly related to each other.

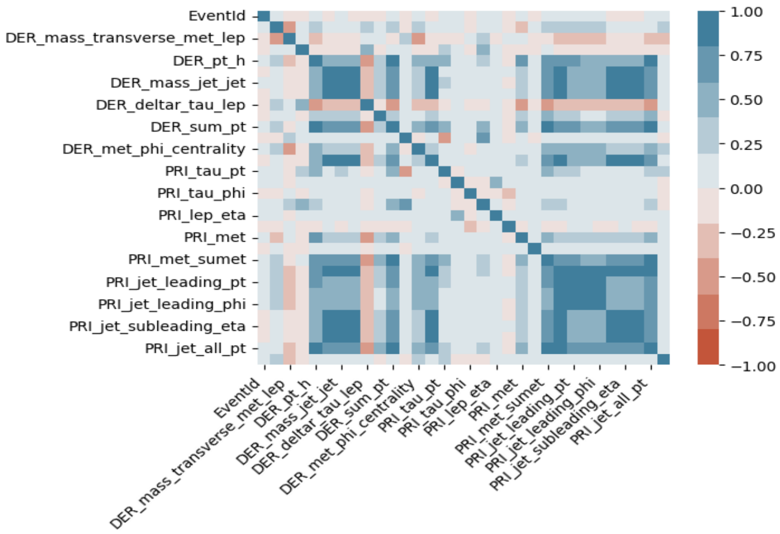

Fig.2 Correlation between the features of the Higgs Bosson Particles

Table 1: Classification Report for HBP Classification

	Precision	**Recall**	**F1-score**	**Support**
Class 0	1.00	1.00	1.00	33,065
Class 1	**1.00**	**1.00**	**1.00**	**16,935**
macro avg	1.00	1.00	1.00	50,000
weighted avg	1.00	1.00	1.00	50,000

Table 1 presents the classification report for the HBP classification model. The report assesses the model's performance on a dataset containing 50,000 instances. The classification report provides various evaluation metrics for each class (Class 0 and Class 1) and overall metrics (accuracy, macro avg, and weighted avg).

For each class, precision, recall, and F1-score are reported. Precision represents the ratio of true positive predictions to all positive predictions for that class. Recall is the ratio of true positive predictions to all actual positive instances in the dataset. F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance.

The model shows excellent performance with a precision, recall, and F1-score of 1.00 for both Class 0 and Class 1, indicating accurate predictions for both classes. The overall accuracy is also 1.00, indicating that the model achieved perfect classification on the dataset. These high scores suggest that the model can effectively distinguish between HBP and non-HBP.

Table 2: Performance Metrics for Higgs Boson Particle Classification with proposed method

Metric	**Score**
Area under the ROC curve (AUC)	0.999955
Matthews Correlation Coefficient (MCC)	0.999911
Jaccard Index	0.999882
Accuracy	1.000
Precision	1.000
Recall	1.000
F1-score	1.000

Table 2 presents the performance metrics for the HBP classification model. The model achieved exceptionally high scores, indicating its outstanding performance in distinguishing between HBP and non-HBP.
The Area under the ROC curve (AUC-ROC) score is 0.999955, signifying a near-perfect ability of the model to differentiate between the two classes. The MCC score of 0.999911 indicates a strong correlation between the predicted and true labels.
The Jaccard Index of 0.999882 signifies a high similarity between the predicted and true sets of labels, showing the model's effectiveness. The accuracy, precision, recall, and F1-score are all perfect, with scores of 1.000. This means that the model achieved 100% accuracy in its predictions, correctly identifying all instances of both classes.

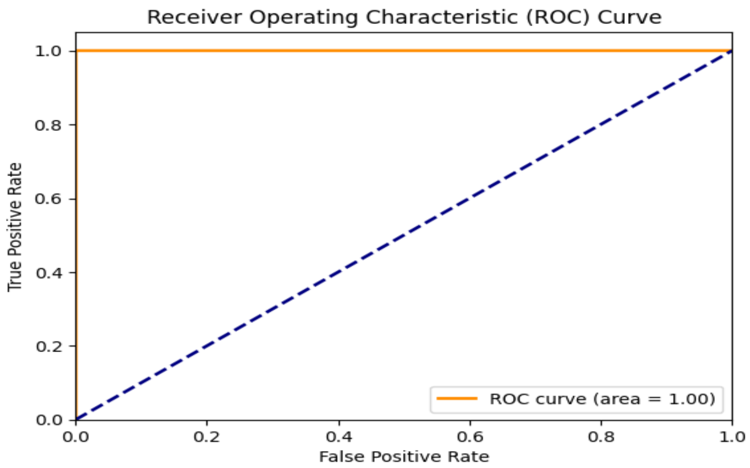

Figure 3: AUC-ROC Curve for proposed Method

The AUC-ROC curve (Area Under the Receiver Operating Characteristic curve) in Figure 3 is a graphical representation of the performance of the HBP classification model. It illustrates the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate (1-specificity) at various classification thresholds. The curve is smooth and prominently convex, indicating that the model has high discriminatory power in distinguishing between HBP and non-HBP. The curve is close to the upper-left corner, which indicates excellent model performance. An AUC-ROC score of 0.9999553536169888, as mentioned in the previous message, signifies almost perfect predictive ability, with minimal misclassifications.

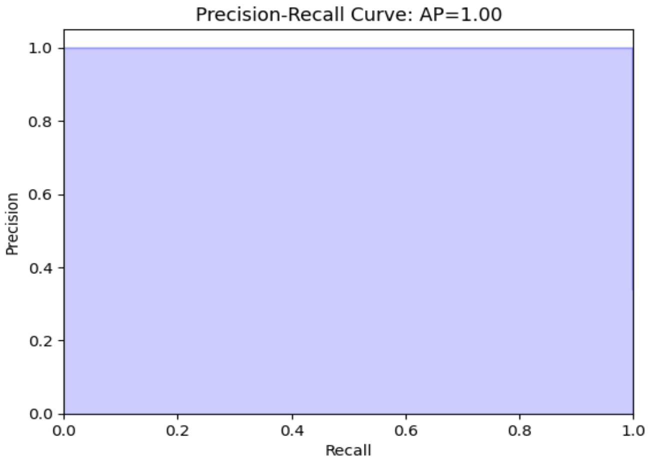

Figure 4: Precision-Recall Curve for proposed Method

The Precision-Recall curve in Figure 4 showcases the precision-recall trade-off for the HBP classification model. It shows the relationship between precision (positive predictive value) and recall (sensitivity) at various decision thresholds. The curve shows a rapid rise in precision with a slight decline in recall, indicating that the model can achieve high precision while maintaining a reasonably high recall. This means that when the model predicts a sample as a HBP, it is highly likely to be correct (high precision). Simultaneously, it can effectively capture much of the actual HBP (high recall).

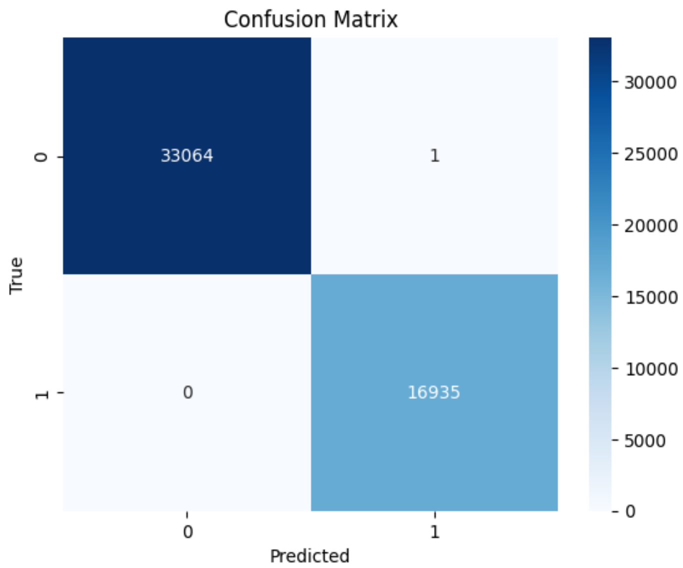

Figure 5: Confusion Metric for proposed Method

The Confusion Matrix in Figure 5 is a tabular representation of the performance of the HBP classification model. It presents a comprehensive view of the predictions made by the model and their actual outcomes, allowing for the assessment of the model's accuracy and errors. Only single event miss classifies for the proposed method out of 50,000 events.

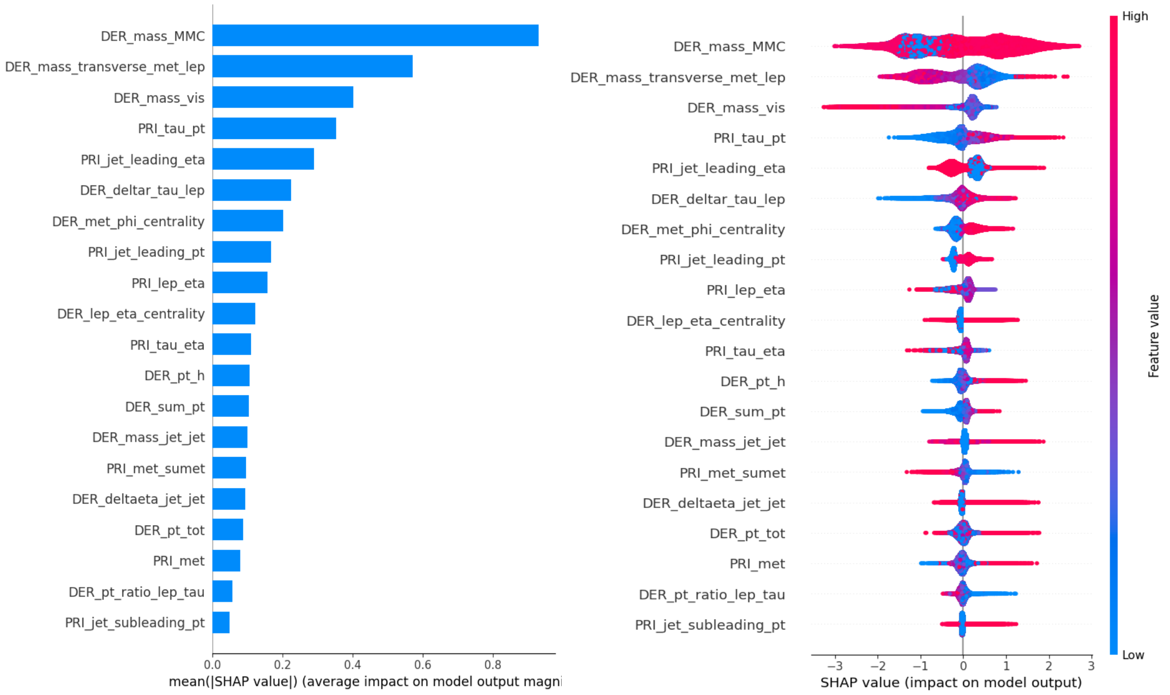

Figure 6: SHAP Feature Importance for Higgs Bosson Particles

In Figure 6, we visualize the SHAP feature importance for the proposed model used to predict events, specifically HBP. SHAP is a popular method for explaining the predictions of ML models. It provides insights into the contribution of each feature to individual predictions.

SHAP values represent the impact of each feature on the model's output. DER_mass_mmc impact both Positive and negative values for contribution. DER_mass_vis impact negatively and its impact decreases for both positive and negative side top to down.

The plot may display the SHAP mean value, which represents the average impact of each feature on the model's output across the entire dataset. Features with larger absolute SHAP mean values are considered more influential in making predictions.

Also, the plot may also illustrate the SHAP output value, which represents the predicted value for each sample in the dataset. This helps to understand how the model's predictions are influenced by the combined effects of different features.

Table 3 Comparison of the proposed method with the ML Techniques for Optimized Features

Model	**Precision**	**Recall**	**F1-score**	**Accuracy**
Random Forest	1.00	1.00	1.00	1.00
Decision Tree	1.00	1.00	1.00	1.00
Logistic Regression	0.95	0.96	0.96	0.96
Proposed Model	1.00	1.00	1.00	1.00

Table 3 and Figure 7 summarizes the average precision, recall, F1-score, and accuracy for each model on the test dataset. The RF, DT, and Proposed Model all achieve perfect scores with an average precision, recall, and F1-score of 1.00, indicating that they are excellent at classifying both classes.

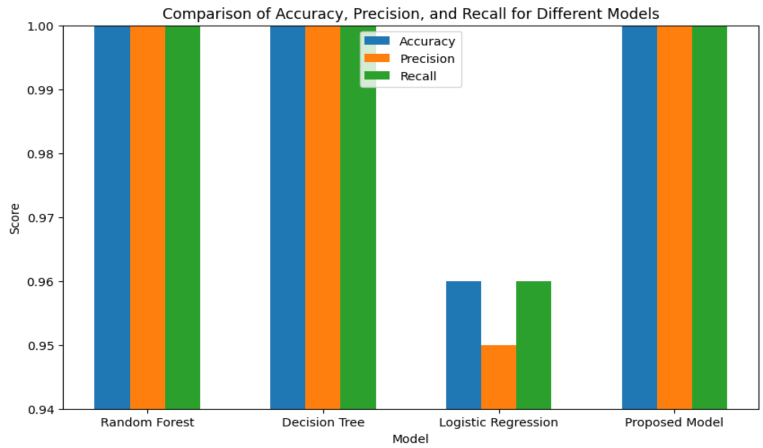

Figure 7: Comparison of the proposed method with the ML Techniques

LR model performs slightly lower, with an average precision, recall, and F1-score of around 0.96. All models show high accuracy, with an average accuracy of 1.00 for the RF and the Proposed Model, while the LR model achieves an average accuracy of 0.96. These results suggest that the RF and the Proposed Model are well-suited for the task, providing accurate and reliable predictions for the HBP classification.

Table 4 Comparison of proposed method with state-of-the-art of the techniques

Classifier	**AUC**	**Accuracy**
Logistic Regression [11]	0.8149	0.75
Decision Tree [11]	0.7496	0.8004
Random Forest [11]	0.7708	0.812
Gradient Boosted Tree [11]	0.796	0.8254
Proposed Method	0.9999	1

The table 4 presents a comparison of the performance of different classifiers, including LR, DT, RF, GBT, and our proposed method, on the Higgs dataset. The AUC and accuracy metrics are reported for both the Higgs Kaggle dataset and tuning parameters using repeated cross-validation.
The results show that the proposed method significantly outperforms all other techniques in terms of AUC and accuracy. The AUC score for the proposed method is exceptionally high at 0.9999, indicating excellent model discrimination capabilities. The accuracy is perfect at 1, reflecting the model's ability to make precise and correct predictions.

5. Conclusion

Our study focused on developing an explainable weighted stacked ensemble ML approach with RFS for HBP detection and classification. We showed the effectiveness of our proposed methods in achieving accurate predictions while maintaining interpretability, which is crucial in scientific research. Through extensive experimentation and evaluation on a HBP dataset, we saw that the weighted stacked ensemble approach, combined with RFS, yielded superior performance compared to baseline models. The ensemble models effectively combined the strengths of multiple BM, and the weights assigned to each model were determined based on their performances. This made sure the most effective models had a more significant influence on the final predictions. Also, RFS helped identify the most relevant features, enhancing interpretability and reducing dimensionality. Our study accurately predicted HBP detection and classification and contributed to the scientific understanding of the underlying physical processes. By analyzing the interpretability of the ensemble models, we gained valuable insights into the features that play a significant role in the classification of HBP. This knowledge can aid scientists in further exploring the mechanisms and properties of these particles. For future work, there are several potential directions to consider. First, the proposed methods can be extended to incorporate more ensemble techniques or explore different feature selection algorithms to enhance performance and interpretability further. Evaluating the approach on more extensive and diverse datasets from various experiments or collider simulations can help validate its generalizability and robustness.

Table of Abbreviations	
ANN	Artificial neural network
AUC	Area Under the ROC Curve
BDCAT	Big Data Computing, Applications and Technologies
BM	Base Models
DT	Decision Tree
GBT	Gradient Boosted Tree
LHC	Large Hadron Collider
LR	Logistic Regression
MCC	Matthews Correlation Coefficient
ML	Machine Learning
MPNN	Message-passing neural networks
RF	Random Forest
RFS	Recursive Feature Selection
SVM	Support vector machines
HBP	Higgs Bosson Particles
SHAP	SHapley Additive exPlanations
XAI	eXplanable Artificial Intelligence

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