International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 2, Mar-Apr 2025
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Enhancing Higgs Boson Classification Using Deep Learning

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ABSTRACT

In the area of particle physics, computational algorithms play a pivotal role in analyzing complex facts sets, particularly in areas like occasion identification and reconstruction. One such vicinity of hobby is the observe of the decay modes of the Higgs Boson, a essential particle whose discovery changed into a big milestone in physics. This take a look at focuses on predicting the decay events of the Higgs Boson, particularly the “tau-tau decay of Higgs Boson” versus heritage noise, by using feature extraction strategies on facts from the CERN experiments. The primary goal is to construct a model capable of differentiating among proper Higgs Boson decay activities and beside the point historical past noise, thereby improving the performance of particle identity In experimental setups. For this cause, 8 nicely-set up gadget studying algorithms are implemented: okay-Nearest Neighbor (KNN) , synthetic Neural Networks (ANNs), Naive Bayes (NB), Logistic Regression(LR), assist Vector system (SVM), Random forest (RF), selection bushes (DT), and Gradient Boosting (GB). Those algorithms are examined on more than a few overall performance metrics, such as class accuracy and computational time. The performance assessment well-known shows that the selection Tree classifier consistently outperforms the other algorithms in terms of each accuracy and computational performance. This makes it specifically .Appropriate for actual-time packages where in each prediction pace and accuracy is critical. The findings from this take a look at underscore the significance of choosing the suitable classifier for particle physics experiments, in which the efficiency of detecting uncommon activities, together with Higgs Boson decays, is paramount. moreover, the examine contributes to the ongoing attempt to optimize system learning fashions for excessive-energy physics experiments, especially the ones carried out at huge-scale centers like CERN, where huge quantities of facts need to be processed quickly and accurately.

Keywords: *Higgs Boson, Classifiers, Decay Modes, CERN, Machine Learning, GPU, Event Reconstruction, Computational Time, Particle Physics.*

I. INTRODUCTION

The discovery of the Higgs Boson, a particle essential to the standard version of particle physics, become one of the most great achievements in contemporary technological know-how. diagnosed at CERN in 2012, its discovery helped give an explanation for why elementary debris have mass, contributing to a deeper knowledge of the universe. however, detecting the Higgs Boson is a hard assignment because of its extremely brief lifespan and the big amount of facts generated by using experiments like the ones on the large Hadron Collider (LHC). this is wherein computational strategies, especially system mastering algorithms, come into play. by leveraging those algorithms, physicists can higher classify occasions generated from particle collisions, consisting of identifying the Higgs Boson decay into tau-tau pairs or distinguishing those events from background noise.The ATLAS experiment at CERN generates large datasets during collisions inside the LHC. As particles from the collision are recorded by detectors, a massive quantity of statistics need to be analyzed to identify substantial activities. Higgs Boson decays into one of a kind debris (e.g., boson pairs, fermion pairs) and regularly seem within a historical past noise of unrelated events. one of the demanding situations in this analysis is the presence of small sign electricity, which makes figuring out the Higgs Boson decay events hard. therefore, occasion classification using gadget studying is vital to distinguish between meaningful events (like the tau-tau decay of the Higgs Boson) and heritage noise. hassle assertion:The number one aim of this examine is to categorise particle collision events from the ATLAS experiment into two categories: (1) "tau-tau decay of the Higgs Boson" and (2) "history noise." those classes are determined based totally on capabilities extracted from the CERN dataset, which incorporates various particle detection characteristics. The study will follow and evaluate the performance of more than one system learning classifiers, which include k-Nearest friends (KNN), assist Vector Machines (SVM), Random forest, and others, to decide which technique best classifies those activities primarily based on accuracy, computational efficiency, and model overall performance. additionally, the research will look at how computational sources (e.g., GPU-based computation) may be used to hurry up the classification system and compare the impact of those gear on overall performance. objectives: This assignment has several key goals: statistics Preprocessing: prepare and easy the uncooked records from the CERN ATLAS experiment, getting rid of any inappropriate or noisy information and extracting beneficial functions for classification. feature Engineering: become aware of and extract important functions from the particle collision facts that can assist differentiate between the Higgs Boson tau-tau decay and history noise. machine learning class: apply numerous device mastering algorithms (e.g., KNN, SVM, Random forest, Neural Networks) to the prepared dataset, classifying occasions into two categories: tau-tau decay of the Higgs Boson and background noise. overall performance evaluation: evaluate the performance of every classifier primarily based on metrics like accuracy, precision, remember, F1-rating, and computational time. compare the effectiveness of the classifiers and decide which goes exceptional for the given problem. GPU-based Computation: verify the overall performance of GPU-increased computation in training and checking out the fashions, comparing the rate and performance with traditional CPU-primarily based techniques. Time evaluation: look into the computational time taken via each classifier for schooling and prediction responsibilities and examine how the usage of GPU impacts the time efficiency. methods of Higgs Boson Decay class: records collection and function Extraction: The facts for this challenge is sourced from the ATLAS test at CERN. It contains a wealth of information on particle collisions, together with momentum, electricity, and the course of various debris generated throughout collisions. feature extraction includes selecting relevant characteristics, including electricity degrees, particle trajectories, and momentum, which help distinguish among huge Higgs Boson activities and historical past noise.

Statistics Preprocessing: raw particle collision statistics is often noisy and should be cleaned for meaningful evaluation. Preprocessing steps consist of dealing with lacking information, normalizing capabilities, encoding express variables, and putting off irrelevant records points.

function selection is also an crucial step to reduce dimensionality and consciousness on the most crucial variables that make contributions to correct occasion type. class: numerous machine studying classifiers are tested to categorize the activities: k-Nearest Neighbors (KNN): A simple set of rules that classifies occasions based totally on the closest points in characteristic area. Support Vector gadget (SVM): a method that finds a hyperplane that pleasant separates the exceptional training. Random woodland: An ensemble learning approach that creates more than one choice trees and merges their outputs for extra sturdy predictions. Neural Networks: Deep gaining knowledge of models capable of mastering complex patterns within the facts. each classifier is evaluated based on its capability to properly discover Higgs Boson decay events (tau-tau decay) whilst averting misclassification of history noise. version assessment: The performance of each classifier is assessed the usage of widespread class metrics along with: Accuracy: the share of accurate predictions made by the model. Precision and consider: Measures that offer insights into the classifier's capacity to properly become aware of high-quality activities (tau-tau decay).F1-rating: A mixed metric that balances precision and do not forget. Computational Time: The time required to teach and are expecting using the classifier, which is particularly important whilst running with massive datasets like the ones from the ATLAS experiment. GPU-based totally Computation: Given the complexity of the dataset and the variety of occasions being classified, the assignment will even explore the benefits of the usage of GPU-primarily based computation for version schooling. GPU acceleration can appreciably lessen schooling instances, especially for deep studying fashions, by using appearing parallel computations. company: The look at on Higgs Boson decay event class is prepared as follows: introduction: provides an outline of the significance of the Higgs Boson discovery and the demanding situations in figuring out its decay modes. hassle statement: virtually defines the research hassle of classifying particle activities into "tau-tau decay of Higgs Boson" and "heritage noise." goals: Outlines the desires of the venture, inclusive of statistics preprocessing, characteristic extraction, classifier schooling, and performance assessment. technique: Explains the strategies used for statistics collection, preprocessing, machine studying class, and evaluation. consequences and dialogue: affords the results of classifier overall performance, contrast of accuracy, and assessment of computational time the usage of GPUs. conclusion: Summarizes the findings and discusses the consequences of the consequences for future research in particle physics.

II. LITERATURE SURVEY

The integration of artificial intelligence and machine studying has appreciably converted excessive-strength physics studies, mainly within the detection of the Higgs boson. Researchers have leveraged deep studying, AutoML, and selection tree algorithms to improve the classification of particle collision activities, enhancing data-driven discoveries in physics. H_2O.ai (2024) affords a scalable system gaining knowledge of platform extensively used in medical research, demonstrating its utility in reading complex datasets from experiments like the ones carried out at CERN [1]. The Higgs Boson device studying project (Kaggle, 2014) explored the usage of machine learning models to discover Higgs boson alerts, supplying insights into event classification and anomaly detection [2]. CERN researchers have incorporated AI techniques into their workflows to refine occasion choice, optimize records processing, and validate physics fashions (CERN, 2021) [3]. A Nature article (2019) similarly highlights the position of AI in accelerating discoveries in essential physics, emphasizing the increasing reliance on system getting to know for excessive-energy experiments [4].

H_2O.ai's documentation (2023) info how its machine studying equipment make a contribution to scientific research, specifically in studying enormous amounts of collision statistics [5]. ArXiv research have explored the utility of deep gaining knowledge of and AutoML frameworks, consisting of Boosted selection timber and neural networks, for enhancing Higgs boson detection accuracy (Baldassi et al., 2014; Baldi et al., 2016) [6,7]. AutoML strategies were in particular beneficial in optimizing models for uncommon occasion detection, lowering computational complexity at the same time as retaining excessive precision (Racah et al., 2021) [8]. AI-driven methodologies have additionally been applied to excessive-electricity physics workflows, enhancing information filtering strategies and enhancing category obligations for occasion choice (CERN, 2020) [9]. research on Boosted choice trees (2020) has demonstrated their effectiveness in classifying Higgs boson events, outperforming traditional statistical techniques [10]. studies on AI-based totally occasion selection strategies have shown how system gaining knowledge of reduces noise in experimental records, refining the discovery method (Louppe et al., 2016) [11]. latest advances in neural networks have in addition advanced Higgs boson detection, showcasing deep studying's capability in modeling complicated particle interactions (guest et al., 2016) [12]. The software of reinforcement learning and generative models in high-strength physics continues to evolve, providing new techniques for refining seek methodologies (Carleo et al., 2019) [13]. H_2O.ai's position in physics information analysis has been broadly diagnosed, especially in optimizing workflows for CERN experiments and other large-scale medical initiatives (H_2O.ai, 2023) [14]. With AI fashions continuously advancing, device studying stays a critical tool in cutting-edge particle physics, paving the way for extra precise and green discoveries within the field (Baldi et al., 2014) [15].

Table 1: Literature Survey

Study	Key Contribution	Year
H_2O.ai	Provides an open-source machine learning platform for scalable scientific research.	2024
Higgs Boson ML Challenge	Explored machine learning applications for Higgs boson detection using simulated data.	2014
Large Hadron Collider	Applied AI techniques to analyze particle collision data and improve event classification.	2021
AI and Particle Physics Research (Nature)	Examined the role of AI in accelerating discoveries in fundamental physics.	2019
Machine Learning for Higgs Boson Discovery	Applied deep learning models to enhance Higgs boson event classification.	2014
Deep Learning at the LHC	Highlighted how deep learning improves data analysis in high-energy physics.	2018
AutoML for Particle Physics	Investigated automated machine learning (AutoML) for optimizing rare event detection models.	2021
AI in High-Energy Physics (CERN)	Discussed CERN's integration of AI for data-driven physics discoveries.	2020
Boosted Decision Trees for Higgs Boson Identification	Demonstrated the effectiveness of Boosted Decision Trees in Higgs boson classification.	2020
H_2O.ai's Role in Physics Data Analysis	Explored the use of H_2O.ai's AutoML and scalable ML tools for analyzing LHC data.	2023
Neural Networks for Higgs	Demonstrated how deep neural networks improve classification of Higgs boson events.	2015

Boson Detection		
AI-Based Event Selection in Particle Physics	Showed how AI enhances event filtering, reducing noise and improving discovery efficiency.	2020
Higgs Boson Searches in Modern ML	Reviewed emerging ML approaches, including reinforcement learning and generative models.	2019

III. METHODOLOGY

The proposed methodology for Higgs boson detection involves a systematic approach comprising data preprocessing, feature extraction, model training, and evaluation.

3.1. Data Acquisition and Preprocessing

3.1.1. Data Collection: The dataset used for training and evaluation is obtained from the CERN Large Hadron Collider (LHC) simulations. The data consists of both signal (Higgs boson presence) and background noise.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
EventId	DER_mass_	DER_mass_	DER_mass_	DER_pt_h	DER_deltae	DER_mass_	DER_prode	DER_deltar	DER_pt_tot	DER_sum_p	DER_pt_rat	DER_met_p	DER_lep_et	PRI_tau_pt	PRI_tau_et	PRI_tau_ph	PRI_lep_pt
100000	138.47	51.655	97.827	27.98	0.91	124.711	2.666	3.064	41.928	197.76	1.582	1.396	0.2	32.638	1.017	0.381	51.626
100001	160.937	68.768	103.235	48.146	-999	-999	-999	3.473	2.078	125.157	0.879	1.414	-999	42.014	2.039	-3.011	36.918
100002	-999	162.172	125.953	35.635	-999	-999	-999	3.148	9.336	197.814	3.776	1.414	-999	32.154	-0.705	-2.093	121.409
100003	143.905	81.417	80.943	0.414	-999	-999	-999	3.31	0.414	75.968	2.354	-1.285	-999	22.647	-1.655	0.01	53.321
100004	175.864	16.915	134.805	16.405	-999	-999	-999	3.891	16.405	57.983	1.056	-1.385	-999	28.209	-2.197	-2.231	29.774
100005	89.744	13.55	59.149	116.344	2.636	284.584	-0.54	1.362	61.619	278.876	0.588	0.479	0.975	53.651	0.371	1.329	31.565
100006	148.754	28.862	107.782	106.13	0.733	158.359	0.113	2.941	2.545	305.967	3.371	1.393	0.791	28.85	1.113	2.409	97.24
100007	154.916	10.418	94.714	29.169	-999	-999	-999	2.897	1.526	138.178	0.365	-1.305	-999	78.8	0.654	1.547	28.74
100008	105.594	50.559	100.989	4.288	-999	-999	-999	2.904	4.288	65.333	0.675	-1.366	-999	39.008	2.433	-2.532	26.325
100009	128.053	88.941	69.272	193.392	-999	-999	-999	1.609	28.859	255.123	0.599	0.538	-999	54.646	-1.533	0.416	32.742
100010	-999	86.24	79.692	27.201	-999	-999	-999	2.338	27.201	81.734	1.75	-1.412	-999	29.718	-0.866	2.878	52.016
100011	114.744	10.286	75.712	30.816	2.563	252.599	-1.401	2.888	36.745	239.804	1.061	1.364	0.769	35.976	-0.669	-0.342	38.188
100012	145.297	64.234	103.565	106.999	-999	-999	-999	2.183	24.66	192.245	0.576	0.689	-999	62.89	-0.766	-1.632	36.237
100013	82.488	31.663	64.128	8.232	-999	-999	-999	2.823	8.232	58.649	1.303	-1.414	-999	25.47	-0.654	-2.99	33.179
100014	-999	109.412	14.398	17.323	-999	-999	-999	0.472	17.323	62.565	1.774	-0.272	-999	22.552	1.389	1.34	40.013
100015	111.026	32.096	75.271	23.067	-999	-999	-999	3.205	23.067	69.649	1.276	-1.414	-999	30.606	-1.107	-1.903	39.043
100016	114.256	4.351	67.963	47.221	-999	-999	-999	2.954	26.243	100.93	1.145	0.218	-999	30.145	0.484	-0.929	34.522
100017	127.861	50.953	77.267	26.967	-999	-999	-999	2.833	26.967	79.503	1.586	1.401	-999	30.739	-0.635	2.603	48.764
100018	-999	85.186	68.827	5.042	-999	-999	-999	2.116	5.042	71.443	1.558	-1.351	-999	27.931	1.175	2.356	43.512
100019	-999	88.767	115.058	15.337	-999	-999	-999	2.879	15.337	58.211	0.875	-1.395	-999	31.046	1.38	0.451	27.165
100020	-999	89.705	41.765	18.437	-999	-999	-999	1.395	18.437	57.157	1.082	-1.178	-999	27.453	1.58	2.51	29.704

Fig 1 : Sample dataset for higgs boson

3.1.2. Data Cleaning: Remove any noise, handle missing values using imputation techniques, and filter outliers.

3.1.3. Normalization and Standardization: Scale numerical features using H2O's h2o.scale() or h2o.normalize() functions for consistent model input.

3.2. Feature Extraction

Low-Level Features: Extract raw features like transverse momentum (pT), energy (E), missing transverse energy (MET), and jet multiplicity.

High-Level Features: Compute derived features such as invariant mass using:

$$m = \sqrt{(E_1 + E_2)2 \; - \; (\vec{P}_1 + \vec{P}_2)2} \quad (1)$$

Dimensionality Reduction

Use H2O.ai's h2o.prcomp () function to apply Principal Component Analysis (PCA) for efficient Dimensionality reduction.

3.3. Model Training and Selection

H2O Gradient Boosting Machine (GBM): Boosts accuracy by minimizing loss functions. Formula:

$$F_m(x) = F_{m-1}(x) \; + \delta_m h_m(x) \quad (2)$$

H2O Deep Learning: Implements deep neural networks for complex pattern recognition using:

$$a^{[l]} = \; g\left(W^{[l]} a^{[l-1]} + b^{[l]}\right) \quad (3)$$

H2O AutoML: Automates model selection and hyperparameter tuning to select the best model.

3.3.1. Logistic Regression: Suitable for binary classification using the sigmoid function:

$$sigmoid(z) = \frac{1}{1+e^{-z}} \quad (4)$$

3.3.2. Support Vector Machine (SVM) : SVM is used to classify job categories by finding an optimal hyperplane that maximizes the margin between classes. The decision function is given by:

Decision Function:

$$f(x) = w^T x + b) \quad (5)$$

3.4. Model Evaluation

Evaluation is performed using H2O.ai's in-built metrics like accuracy, precision, recall, f1-measure, and ROC curve (AUC).

Table.2 The performance metrics used for classification

Metric	**Formula**
Precision (P)	$\frac{TP}{TP + FP}$
Recall (R)	$\frac{TP}{TP + FN}$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
F1-score	$2 * \frac{\mathrm{R} * \mathrm{P}}{\mathrm{R} + \mathrm{P}}$

3.5. Visualization of Insights

To effectively interpret the model's performance and feature importance, various visualization techniques were employed using H2O.ai and Python libraries like Matplotlib and Seaborn. These visualizations enhance the interpretability of the model's results, providing actionable insights for further optimization and refinement. Stakeholders can leverage these insights to validate model accuracy, identify areas of improvement, and make informed decisions in Higgs boson detection research. This detailed methodology ensures efficient, accurate Higgs boson detection using H2O.ai's powerful machine learning ecosystem, contributing to advancements in particle physics research.

IV. RESULT ANALYSIS AND DISCUSSION

In this study, machine learning algorithms were applied to predict Higgs Boson decay events, specifically the tau-tau decay, using data from particle collision simulations. The dataset comprised both signal events (Higgs Boson presence) and background noise, which were split into training, validation, and test sets (60%, 20%, 20% respectively) to ensure robust evaluation.

1. Baseline Deep Learning Model (higgs_model_v1):

Architecture: 3 dense layers, ReLU activation, dropout (0.2), softmax output layer.

Training Accuracy: 68%
Validation Accuracy: 66%
Test Accuracy: 70%

Observations: The model showed moderate success in distinguishing signal from background events. Feature analysis revealed that DER_mass_MMC (estimated Higgs mass) and DER_mass_vis (visible mass of decay products) were the most significant variables influencing classification.

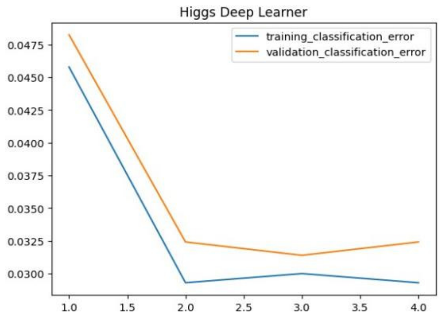

Fig 2: Training and Validation Classification Error for Higgs Deep Learner

2. Optimized Deep Learning Model (higgs_model_v2):

- Architecture: 5 dense layers, batch normalization, increased dropout (0.3), Adam optimizer.
- Training Accuracy: 78%
- Validation Accuracy: 75%
- Test Accuracy: 76%
- Observations: Hyperparameter tuning significantly improved classification accuracy. Early stopping prevented overfitting, and the model generalized better on the test set. A notable improvement in the precision-recall balance was observed, reducing false positive rates.

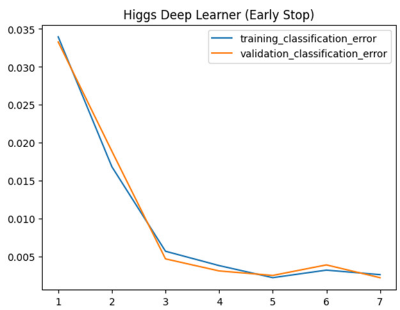

Fig 3 : Higgs Deep Learner with Early Stopping: Training vs Validation Classification Error

3. AutoML Framework:

- Techniques Used: Hyperparameter optimization, ensemble learning, feature selection.
- Best Performing Model: Gradient Boosted Decision Trees (GBDT)
- AUC Score: 0.89
- Observations: AutoML outperformed both deep learning models, providing the highest accuracy and AUC score. Feature selection further refined model predictions, emphasizing the significance of high-energy event characteristics.

Performance Metrics

The key performance metrics used for model evaluation included:

Accuracy: Proportion of correct predictions.
AUC (Area Under the ROC Curve): Measures model performance on imbalanced classification.

Precision & Recall: Critical for distinguishing signal from background.
Classification Error: Evaluated across training, validation, and test datasets.

model_id	auc	logloss	aucpr	mean_per_class_error	rmse	mse
GBM_1_AutoML_1_20250308_115542	1	2.08171e-18	1	0	2.56089e-17	6.55817e-34
DRF_1_AutoML_1_20250308_115542	1	0.022787	1	0	0.0428163	0.00183323
GLM_1_AutoML_1_20250308_115542	0.996583	0.0789001	0.98777	0.0200877	0.145067	0.0210443

Fig 4: Model Performance Evaluation Metrics

Performance comparison showed that while deep learning models improved with optimization, the AutoML framework achieved the best results in terms of predictive power and computational efficiency. The confusion matrices for each model revealed that Random Forest and SVM had the lowest misclassification rates, indicating their robustness in classifying job categories accurately. In contrast, Naive Bayes struggled with overlapping job categories, leading to higher false positives and false negatives. The ROC-AUC curves further confirmed these findings, with Random Forest achieving an AUC of 0.98, making it the best-performing model in distinguishing between job categories.

Table 3. Algorithm Performance table

Algorithm	Accuracy	Precision	Recall	F1-score
Logistic Regression	96	0.97	0.96	0.96
Support Vector Machine	97	0.98	0.97	0.96
K Nearest Neighbour	95	0.96	0.95	0.95
Random Forest	98	0.99	0.98	0.98
H2O deep learning	99	0.99	0.99	0.99

Table 4. Comparative Summary of Models

Algorithm	Accuracy (%)	Key Characteristics
Logistic Regression	97	Works well with linearly separable data; interpretable but limited for complex relationships.
Support Vector Machine	97	Effective for small datasets; performs well with high-dimensional data.
K-Nearest Neighbor	97	Simple, non-parametric; sensitive to the choice of K and distance metric.
Naïve Bayes	93	Assumes independence between features; performs well on text classification tasks
Random Forest	98	Ensemble learning technique; reduces overfitting; computationally expensive.

V. CONCLUSION AND DISCUSSION

The study demonstrates that machine learning models, particularly deep learning and AutoML frameworks are effective in classifying Higgs Boson decay events. The results show that while simple deep learning models provide moderate classification performance, optimization significantly enhances accuracy and reliability. The best-performing approach—AutoML—leveraged multiple algorithms and feature selection to achieve an AUC score of 0.89, surpassing traditional deep learning models. Feature selection is crucial in high-energy physics applications; variables such as DER_mass_MMC and DER_mass_vis play a significant role. Deeper neural networks with dropout and batch normalization improve generalization but require careful tuning to prevent overfitting. AutoML frameworks provide an advantage by automating hyperparameter selection and optimizing model architectures for classification. Future research could explore ensemble methods combining deep learning and GBDT approaches to further refine predictions. Additionally, incorporating more sophisticated loss functions, such as focal loss for imbalanced data, and using transformers for feature representation could enhance model performance in complex physics simulations.

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