Article

Efficient anomaly heartbeat detection approach for intermediate nodes of internet-of-things platforms

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Abstract: This work focused on the evaluation of some machine learning (ML) models and their application in e-health, using intermediate nodes within an Internet of Things (IoT) platform used for heartbeat anomaly detection. For the evaluation of ML models, a set of statistical validation metrics was selected. These metrics were applied in the training, testing and validation phases of the models. The results obtained can determine relevant factors for the selection of ML models, either based on the statistical and intrinsic efficiency of the ML models, or on their suitability to be implemented in intermediate nodes within an IoT platform. the more Lightweight models such as Simple Linear Regression, Logistic Regression, and K Nearest Neighbors, could easily operate in intermediate nodes, and they are models that require low processing and storage to work. In conclusion, the approach for intermediate nodes of Internet of Things platforms using cognitive networks decreases the processing cost in cloud computing and transfers it to the fog layer.

Keywords: Machine Learning; Fog layer; Heartrate; Performance; IoT

1. Introduction

For many authors, the beginning of the fourth industrial revolution was given by the rise of Internet of Things (IoT) platforms, the increased use of IoT platforms, which promises various changes in all aspects of human life and especially in the healthcare industry [1,2]. IoT can help provide access to many services, such as remote monitoring from many locations, thanks to its ubiquity feature. IoT presents different challenges when implementing e-health applications and tools; for example, the large number of sensors and heterogeneous networks that compose IoT platforms generate large volumes of data; these volumes are characterized by velocity, volume, variety, value, and veracity [3,4,5].

There are other challenges when it comes to implementing e-health applications in IoT, where latency plays a critical role in making life-saving decisions. Although cloud environments have the computational capacity to resolve and interpret large volumes of data at very low latencies, the implementation of e-health applications in these environments comes with limitations in terms of multi-hop distance from the data source, so it must be ensured that at least the most critical part of the overall service is always available to the patient, even in the presence of hostile environments with intermittent or no network connectivity to the Cloud without neglecting privacy, which aims to protect the user's sensitive health-related data [6,7,8].

In recent years, artificial intelligence (AI) has been proposing solutions to some of the challenges of e-health in a disruptive and effective way, the main challenge for AI implementation in IoT platforms is resource consumption, as it requires cost and computational complexity to achieve its objectives [9,10]. AI and ML model implementation techniques require a high number of memory resources and computational (processing) capacity for training large models. However, some new algorithms and lighter ML models are being

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designed or adapted so that they can work more efficiently on devices with limited computational capabilities, requiring less storage resources and computational power [11,12,13].

Machine Learning (ML) is one of the AI techniques that has been applied in different fields, including e-health, the inclusion of ML models in the classification and prediction of heartbeat, can contribute to the improvement of quality of life [14, 15]. According to the World Health Organization (WHO), diseases associated with heart failure (heart disease) are one of the chronic Non-Communicable Diseases (NCDs) that can affect all people of all ages. The NCDs together account for nearly 70% of deaths worldwide. According the WHO also warns that due to NCDs, almost 86% of the 17 million people who die prematurely are in low-or middle-income countries [16], as is the case of Colombia where this work is being developed.

AI techniques mixed in distributed computing environments can be a solution to the challenges posed by e-health applications and their approach based on multi-architectures [17]. This work focused on the evaluation of some of the classification and regression models used for the anomaly detection; we had a groups of metrics the group of metrics, are the statistical metrics where accuracy, precision, recall, specificity, F1 score and AUC were taken into account [18,19].

2. Materials and Methods

For the implementation of the IoT platform scenario, two types of nodes were used, cloud nodes (server's nodes) and intermediate nodes (Raspberry Pi3 and Mini Pc -Intel Celeron 2.0 GHz, and, 2 GB on memory ram), these nodes were hosted in Telemedicine Research Group (TIGUM) location, show Figure 1. The evaluation of the ML models was performed according to two groups of metrics, the first group of metrics corresponds to the metrics shown in the table, these statistical metrics allow us to determine if the models will do a good job of detection or prediction for new and future target data.

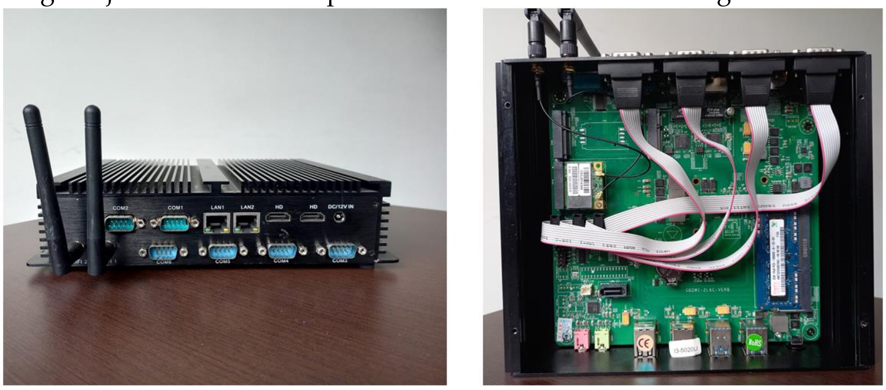

Figure 1. Intermediate nodes design

Figure 2 shows the architecture proposed and developed for the implementation of the IoT platform to be evaluated, this consists of an upper layer called Cloud layer, where the largest capacity in terms of storage and processing (computational resources) are located, in this layer are carried out all the activities that require higher computational costs and the requirement of services or applications allows a higher latency. The second layer called Fog, is a layer that has some processing and storage resources in smaller quantities than the cloud layer, in fog activities that require an intermediate computational cost are carried out. At the edge are the devices that connect with sensors and people, this layer called edge, has few storage and processing resources, but allows performing low computational cost jobs at very low latencies.

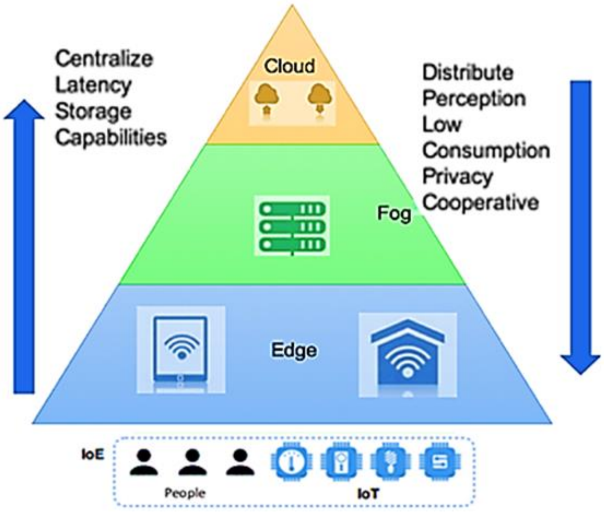

Figure 2. Internet of Things platform architecture

The statistical metrics were implemented in the training and testing-validation phases, the metrics were extracted by implementing a tool in Python 3.9.5, whose objective was the classification and detection of heartbeat anomalies, based on the results of the two data sets that supported this experiment. The models used for this study are listed in Table 1.

Table 1. Machine learning models

Machine learning models	Acronym
Simple Linear Regression	SLR
Logistic Regression	LR
K Nearest Neighbors	KNN
Stochastic Gradient Descent	SGD
Naive Bayes	NB
Decision Tree Classifier	DT
Random Forest	RF
Extremely Random Trees	ETC
Gradient Boosting Classifier	GBC
XG Boost Classifier	XGBC
Sequential Model Neural network	SNN
Multi-layer Perceptron Neural Network	MLP

2.1 Data set

Two datasets were used in this work, the first dataset used is available in [20], this study selected potential participants (115) between 18 and 90 years old, this dataset shows on average 36300 measurements per individual, Age, blood pressure, heartbeat rate, sample time and BMI. Within the study informed consent was obtained from all participants [21]. The second data set was obtained from the Fluke Biomedical Patient Monitor Simulators (PS420) this set was obtained with the same biomedical signals as the first set. Personal data, such as age, gender, height, and weight, were collected prior to data collection and this information, along with the collected sensor readings, were anonymized and stored in accordance with HIPAA [22,23].

Some key features characteristic of PS420 patient simulator, are: small enough to fit in a pocket, the handy it features a wide variety of simulation capability, including a full range of ECG, respiration, blood pressure, temperature and cardiac output conditions. The tool includes 12-lead ECG, two-channel blood pressure simulation, 35 arrhythmia selections, pacemaker simulation as well as adult and pediatric normal sinus rhythms, ECG performance waveforms, ST segment levels, ECG artifact, etc. This tool has 12 Lead ECG with nine independent outputs referenced to RL. The Table 2 shows some specifications of PS420 patient simulator [24].

Table 2. Some specifications of PS420 patient simulator.

ECG	Details
Normal rate	80 BPM
Selectable rates	30, 40, 60, 80, 100, 120, 140, 160, 180, 200, 220, 240, 260, 280, and 300 BPM
Accuracy	± 1 %
Output impedance	500 Ω, 1000 Ω, 1500 Ω, and 2000 Ω for Leads I, II, and III
ECG amplitudes	0.5 mV, 1 mV, 1.5 mV, and 2 mV
Amplitude accuracy	± 2 % Lead II
Arrhythmias	
	PVC2 early, RV focus*
Base rate of 80 BPM	PVC2 R on T, RV focus*
Sinus arrhythmia	Multifocal PVCs*
Atrial (PAC)*	Atrial fibrillation coarse/fine
Missed beat*	PVCs 6/minute
Atrial tachycardia	PVCs 12/minute
Atrial flutter	PVCs 24/minute
Nodal (PNC)*	Frequent Multifocal PVCs
Nodal rhythm	Bigeminy
Supraventricular tachycardia	Trigeminy
PVC1 left ventricular focus*	Pair PVCs*
PVC 1 early, LV focus*	Run 5 PVCs*
PVC1 R on T, LV focus*	Run 11 PVCs*
PVC2 right ventricular focus*	Ventricular tachycardia
Conduction defects	Ventricular fibrillation (coarse
First degree	and fine) on all leads except
Second degree	Lead III
Third degree	Asystole
	Right/Left bundle branch block

2.2 Data cleaning

The data sets were treated with to adjust records without value, duplicates or corrupted, with the clean data sets, the prevalence calculation was performed in the output function and, this function contains, values between 0 and 1, where the patients found with the presence of a heartbeat anomaly are identified with the number 1, the prevalence yielded a value of 0.5, which indicates that 50 % of the readings of the data set contain data with the features of a heartbeat anomaly. Prevalence is the percentage of samples that have the target characteristic to be predicted, as shows in the equation.

$$prevalence = \frac{\sum_{i=1}^{n} yi}{i} \quad (1)$$

The data set obtained was divided into two sets (Training and validate), the training set with 70% and the validate set with 30% [25]. Once the subset of data has been obtained,

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the prevalence calculation is performed, yielding 0.519 for the training set, 0.659 for validation, as the objective is to train a model that classifies correctly and the previous one shows that the majority class does not reflect heartbeat anomalies, For the above reason, a balancing of the data set is carried out, so that the training team has the same number of random results with a positive value (Heartbeat anomaly) and a negative value for patient without anomalies.

2.3 Metrics

The accuracy of a classification can be evaluated by calculating the number of correctly recognized class examples, those are true positives (tp), the number of correctly recognized examples that do not belong to the class are true negatives (tn), and examples that were incorrectly assigned to the class are false positives (fp), or that were not recognized as class examples are false negatives (fn) [25]. To carry out the evaluation of the models, two groups of metrics were taken, the first group of metrics is oriented to the measurement of performance, through accuracy, precision, specificity, recall and F1 − score; the Table 3. shows the measure, formula and general definition.

Table 3. Metrics

ML models	Formula	Description
Accuracy	$\frac{(tp+tn)}{(\mathrm{tp}+\mathrm{tn})}$	Overall effectiveness of model
Recall	$\frac{tp}{(\mathrm{tp}+\mathrm{tn})}$	Class agreement of the data labels with the positive labels given by classifier
Specificity	$\frac{tn}{(\mathrm{tp}+\mathrm{tn})}$	Effectiveness of a classifier to identify positive labels
Precision	$\frac{tp}{(\mathrm{tp}+\mathrm{fp})}$	How effectively a classifier identifies negative labels
F1 - Score	$2*\frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}}$	Weighted average of the precision and recall
AUC	$\frac{1}{2}*\frac{tp}{(\mathrm{tp}+\mathrm{fn})}+\frac{tn}{tn+fp}$	Classifier's ability to avoid false classification

3. Results

Results in training stage, are presented in Table 4. Three models with high accuracy can be identified for this training stage, XGBC, RF AND GB whit 1.0. The models that presented the lowest accuracy values for this metric were KNN 0.79, SGD and NB with 0.82. For the F1-score metric, the three most relevant models were DT, GB and XGBC all with 1.0; on the other hand, the models with the lowest values in this metric were KNN with 0.80, SGD and NB with 0.83. In general, all the models evaluated for the training stage are in the fourth quarter (0.75 - 1.0), which represents a good performance in the classification of cardiac anomalies within the data sets used.

Table 4. Training models results.

Model	Data_set	AUC	Accuracy	Recall	Precision	Specificity	F1-score
SLR	train	0,9147	0,8352	0,8571	0,8211	0,8132	0,8387

LR	train	0,9163	0,8352	0,8462	0,8280	0,8242	0,8370
KNN	train	0,9003	0,7967	0,8242	0,7813	0,7692	0,8021
SGD	train	0,9140	0,8297	0,8462	0,8191	0,8132	0,8324
NB	train	0,9022	0,8297	0,8571	0,8125	0,8022	0,8342
DT	train	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**
RF	train	**1,0000**	0,9945	**1,0000**	0,9891	0,9890	0,9945
GB	train	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**
XGBC	train	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**	**1,0000**
ETC	train	0,9679	0,8736	0,8901	0,8617	0,8571	0,8757
SNN	train	0,9482	0,9451	0,9560	0,9355	0,9341	0,9457
CLF	train	0,9873	0,9615	0,9231	**1,0000**	**1,0000**	0,9600

Table 5 shows the results for intermediate nodes in stage of validation, for this case highly accuracy models are: LR, ETC and SNN with 0.85, and NB, XGBC with 0.87; DT 0.65 and GB with 0.84 presented the lowest values for this metric. For the F1-score metric, the NB and XGBC with 0.90, ETC with 0.89, are the models show the highest performance values; the models with the lowest performance were DT with 0.72, GB and CLF with 0.85. In this phase, not all models were able to obtain metrics that are in the last quarter (0.75-1.0). This is the case of DT, RF and SLR, which in some of the metrics did not achieve a threshold equal to or greater than 0.75.

Table 5. Validation models results.

Model	Data_set	AUC	Accuracy	Recall	Precision	Specificity	F1-score
SLR	valid	**0,9153**	0,8293	0,8889	0,8571	0,7143	0,8727
LR	valid	0,9127	**0,8537**	0,8889	0,8889	**0,7857**	0,8889
KNN	valid	0,9087	0,8293	**0,9259**	0,8333	0,6429	0,8772
SGD	valid	**0,9206**	0,8293	0,8889	0,8571	0,7143	0,8727
NB	valid	**0,9206**	**0,8780**	**0,9259**	**0,8929**	**0,7857**	**0,9091**
DT	valid	0,6548	0,6585	0,6667	0,7826	0,6429	0,7200
RF	valid	0,8677	0,8293	0,8889	0,8571	0,7143	0,8727
GB	valid	0,8624	0,8049	0,8889	0,8276	0,6429	0,8571
XGBC	valid	0,8598	**0,8780**	**0,9259**	**0,8929**	**0,7857**	**0,9091**
ETC	valid	0,8386	**0,8537**	**0,9259**	0,8621	0,7143	0,8929
SNN	valid	0,9021	**0,8537**	0,8519	**0,9200**	**0,8571**	0,8846
CLF	valid	0,8796	0,8293	0,7778	**0,9545**	**0,9286**	0,8571

AUC and ROC analysis is one of the most important evaluation metrics to verify the performance of any classification model. ROC is given by the receiver operating characteristics, while AUC is given by the area under the curve [26]. The Figure 3 shows the results in the training and validation stages for all the models evaluated; in it we can observe two types of behaviors, the first one is a group of models SLR, KNN, LR, SGD, ETC and NB, where the performance of the training and validation metrics behaves in an assimilated way. The second group of models CLF, DT, RF, GB, XGBC, SNN and CLF, present a higher performance in the training stage and then this performance decreases considerably in the validation stage.

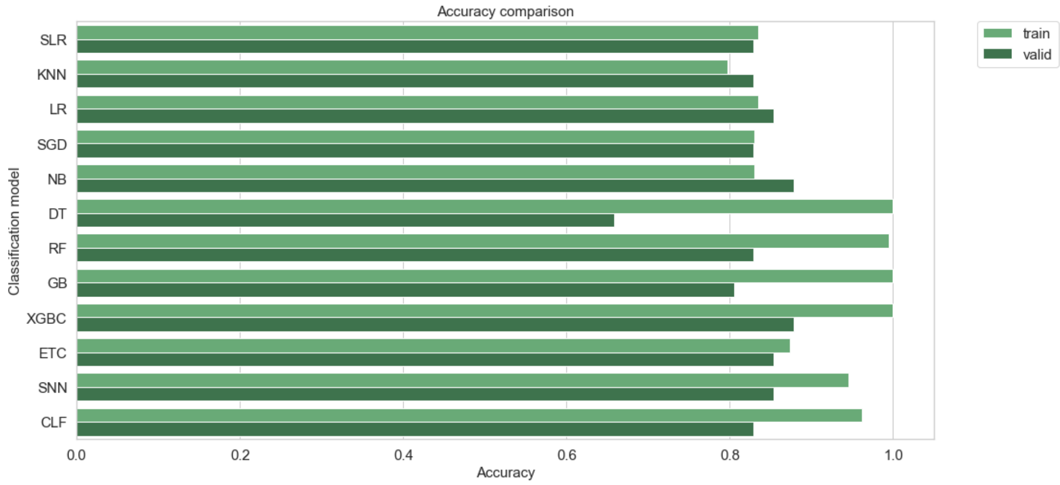

Figure 3: Accuracy comparison

Figure 4 shows the AUC comparison with general performance of the models in the two stages, this method is convenient for the following reasons: It is scale invariant, it measures how well the predictions are ranked, rather than their absolute values. It is invariant with respect to the classification threshold, it measures the quality of the model predictions, regardless of which classification threshold is chosen. as well as the accuracy evaluation, there are two types of behavior, one group and models that maintain similar behaviors in the two stages, such as SLR, LR, KNN, SGD, NB and SNN, the other group shows a difference between the performance achieved in the two stages, this is the case of DT, RF, GB, XGBC, ETC and CLF.

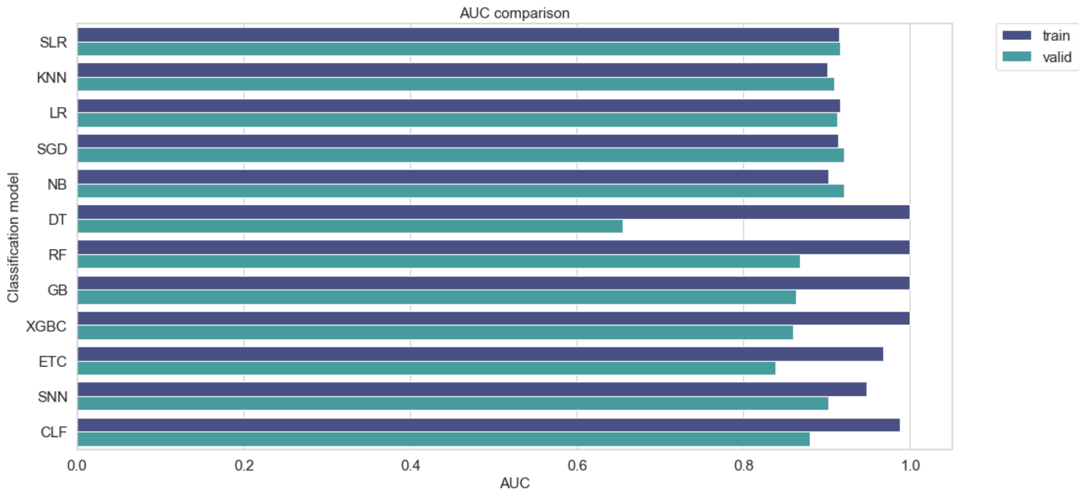

Figure 4: AUC comparison

Finally, Figure 5 shows the ROC comparison behavior of the models according to the Fp and Tp, obtained in the validation stage, this metric shows the group of models LSR, LR, KNN and CLF, with a high performance and stability, while the DT, ETC and XBGC models, show the lowest performance.

$$1 - especifity = \frac{\text{Fp}}{\text{Tp+Fp}} \qquad (2)$$

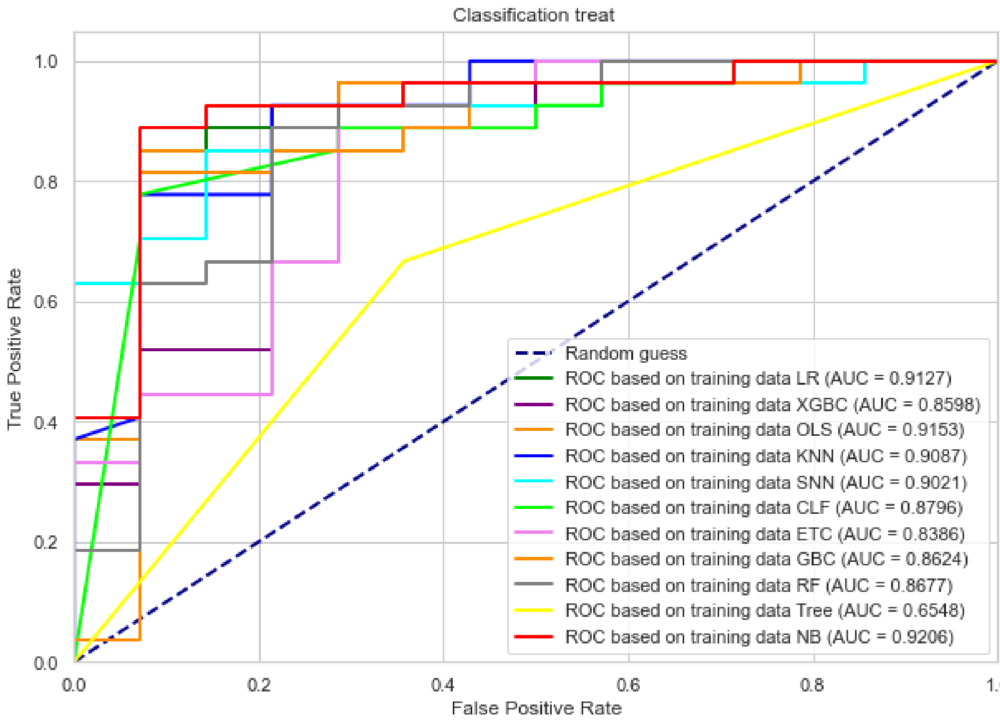

Figure 5: ROC comparison. Supplementary material.

4. Conclusions

This study was able to demonstrate the effectiveness of the new design of the FOG layer of an intermediate biosignals processing node with cognitive networks applied to an Internet of Things architecture. The results show that the lighter models such as LSR, LR and KNN are highly functional and require low processing and heap storage capacity.

For the comparison of the models, the cross-validation mechanism was presented as a tool that allowed us to test the generation of the models; in it, all the evaluated models met the accuracy threshold, allowing reliable estimates to be obtained for the detection of possible heartbeat anomalies, both for the testing and validation sets.

It is important to highlight that all the models evaluated can classify cardiac anomalies with great precision, with the exception of DT and RF, which in the validation stage presented metrics lower than 0.75, being below the 4th percentile.

Finally, with this new efficient approach detection of abnormal heartbeats is very important for early diagnosis in places whose connection to IoT networks are precarious. With the help of ML, the detection allows obtaining data that guides the possible diagnosis.

Supplementary Materials: The results tables in excel format.

Author Contribution: One author research. The author has read and agreed to the published version of the manuscript.

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Appendix A

Supplementary data: a date results of machine learning proofs.

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