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Machine Learning–Enabled Rupture Risk Prediction in Aortic Aneurysms Using Imaging Biomarkers and Clinical Profiles

Dr. Suresh Palarimath[1], G. Vanaja Kumari[2] , M. Kamarajan[3] , Sonali Kothari[4]
[1]Lecturer, College of Computing and Information Sciences, University of Technology and Applied Sciences Salalah, Dhofar, Salalah, Sultanate of Oman,
Email ID : suresh.palarimath@utas.edu.om
[2]Computing Technologies,SRM Institute of Science and Technology, Kattankulathur, Chennai,
Email ID : sivas.postbox@gmail.com
[3]Assistant Professor, Electronics and Communication Engineering,Vels Institute of Science, Technology and Advanced Studies, Chengalpattu, Chennai, Tamil Nadu,
Email ID : mkamarajan75@gmail.com
ORCHID ID:0009-0003-2147-9209
[4]Associate Professor, Computer Science and Engineering, Symbiosis Institute of Technology
Pune, Maharashtra,
Email ID : sonalikothari@gmail.com

ABSTRACT
The rupture of aortic aneurysms is a life-threatening and most fatal condition and predicting them is a major concern in clinical practice. The traditional risk assessment protocols are mainly based on the diameter of an aneurysm, which does not capture the biomechanical and clinical variance in patients adequately. This paper suggests a machine learning-based architecture of rupture risk forecasting in aortic aneurysms through combination of imaging biomarkers using computed tomography angiography with a detailed clinical history. The data set was analysed on a retrospective basis of 620 patients and includes morphological and biomechanical imaging features in addition to demographic as well as clinical variables. Four monitored learning schemes; Logistic Regression, Support Order machine, Random forest, and Extreme Gradient Boosting (XGBoost) were composed and assessed. Experimental findings indicated that the ensemble-based models performed better than the linear models where XGBoost had the best performance of not only 89.4% accuracy, sensitivity of 0.86, specificity of 0.91, but also an area under the receiver operating characteristic curve (AUC) of 0.92. The analysis of the importance of features the most prominent predictors of rupture were found to be peak wall stress, aneurysm diameter, intraluminal thrombus volume, and growth rate. The framework presented in the research demonstrated a significant improvement in predictive accuracy over traditional methods that rely on the diameter-based and statistical methods. The results reveal the clinical possibilities of multimodal risk stratification based on machine learning to aid personalised decisions and outcomes in the treatment of aortic aneurysms.
Keywords: Aortic aneurysm, rupture risk prediction, machine learning, imaging biomarkers, clinical decision support..

1. INTRODUCTION:

Aortic aneurysms are a serious cardiovascular disease, which is characterised by the abnormal expansion of the aortic wall, and there is a high risk of its rupture leading to high mortality rates. Although diagnostic imaging and clinical management have improved, it is quite challenging to successfully predict aneurysm rupture, and this is one of the biggest problems in the field of vascular medicine [1]. The contemporary usage of clinical judgment is mostly based on the easy anatomical criteria of the largest diameter of the aneurysm and its velocity of increase. Nevertheless, several researchers have demonstrated that rupture is possible in an aneurysm with a size smaller than the suggested intervention, and many of the large aneurysms are asymptomatic, which has raised the shortcomings of the traditional risk evaluation methods. New advances in medical imaging now allow the elicitation of high-order imaging biomarkers, such as aneurysm structure, walls stress distribution, intraluminal thrombus, and tissue heterogeneity [2]. Such biomarkers are a more detailed reflection of biomechanics and pathological course of aneurysms, compared to diameter. Simultaneously, patient-related clinical profiles (age, sex, blood pressure, smoking history, genetic predisposition, and co-morbidities) are major factors contributing to behaviour and estimation of aneurysm rupture. The combination of these heterogeneous sources of data creates large analytical complexity that traditional statistical models cannot handle. Machine learning (ML) provides an effective paradigm on how to tackle this complexity by detecting non-linear motifs and dynamics in high-dimensional data streams [3]. The use of ML-empowered predictive models capable of integrating imaging-based biomarkers with clinical variables enables the creation of personalised estimates of ruinous risk to be used in precision medicine in vascular services. These models can enhance predicting high-risk patients at an

early stage, optimize surveillance cycles, and inform patients of proper intervention, which in turn can eliminate unnecessary operations and catastrophic rupture occurrences. The study is aimed at the formulation and testing of an artificial intelligence-based scenario of predicting rupture in aortic aneurysms through multimodal imaging biomarkers and clinical characteristics. The proposed solution will inform clinicians with the help of data-driven decision tools that go beyond diameter metrics to risk stratification according to patient characteristics to improve clinical outcomes and resource use in the management of aneurysms ultimately.

2. RELATED WORKS

The recent developments in the field of cardiovascular research placed an increased importance on the combination of computational modelling, current imaging, and artificial intelligence to enhance the risk prediction and personalised clinical decision-making in vascular diseases. Within the setting of aortic aneurysms, the dichotomy of standard diameter based assessment has been heavily criticised to be insufficient to reflect patient-specific rupture, so methods of exploring the information of data-driven and biomechanically aware assessment methods are being actively sought. Computational hemodynamics has become one of the primary areas of research in the knowledge of aneurysm development and rupture. The significance of flow descriptors like wall shear stress, oscillatory shear index and pressure gradients in vascular pathology characterisation was signified by Ene-Iordache Bogdan [15]. These hemodynamic variables can give a mechanistic understanding of aneurysm wall degeneration and are in addition to purely geometrical indicators. Equally, Hu et al. [19] conducted a literature review of computational fluid dynamics (CFD) modelling of aortic aneurysms and dissection showing that patient-specific simulations can identify high-risk flow patterns and stress concentration in rupture. Fluid structure interactionist models build upon this paradigm theme further by linking blood flow with vessel wall mechanics and their systemic discussion [25] by Mourato et al. which has now been but sparsely exploited in clinical applications in the recent past. The imaging technologies have expanded the range of biomarkers used in the evaluation of cardiovascular risks. Multi-modality imaging can be assessed using CT, MRI and PET which allow such detailed assessment of vascular morphology, tissue composition and functional parameters. The study of Goldie et al. [17] showing that multiple imaging techniques can be used to enhance phenotyping in hypertrophic cardiomyopathy can be applied to the study of aneurysms. Moreover, Giacobbe et al. [16] emphasized the role of gender medicine in clinical radiology and revealed that imaging characteristics and disease distribution may be sex-specific and affect the quality and correctness of diagnoses. Such results can be of special significance in current applications of the prediction of ruptures caused by aneurysms as the rupture rates and progression vary in men and women.

Aneurysm heterogeneity has also been better understood through the biological and molecular perspectives. Mathias et al. [24] investigated the possibility of embryological difference and molecular pathways that distinguish thoracic and abdominal aortic aneurysms and found that stratified modelling should be applied. In line with this, Hu et al. [20] talked about the use of spatial omics in cardiovascular studies and provided the new possibilities of molecular data interactions with imaging and clinical variables. Herzog et al. [18] thoroughly discuss vascular aging and arterial stiffness, which are considered considerable risk factors in the susceptibility of the aneurysms to aneurysm, and proof that the biomarkers of stiffness are relevant to productive prediction. Artificial intelligence has also become used more and more in cardiovascular medicine assisting in accuracy in diagnostics, as well as, predicting outcome. According to Kolaszyńska and Lorkowski [22], it was a scoping review of AI in cardiology and atherosclerosis, which showed a consistent improvement in performance compared to traditional statistical techniques. The article by Leivaditis et al. [23] in a different area of surgery has demonstrated the effects of AI-assisted decision support systems, which are revolutionizing cardiac surgery because they enhance risk classification and pre-operative deviation planning. These tendencies correspond to the expanded use of AI in neurovisualization or risk surveillance, as the review by Omarov and Aliyeva [26] suggests, and support the idea that machine learning can be diversified to more challenging biomedical prediction tasks.

3. METHODS AND MATERIALS

The present study uses a retrospective machine learning-based study design by identifying rupture risk of aortic aneurysms by combining imaging biomarkers and patient-specific clinical profiles. The complete popularity involves the data gathering, pretreatment, attribute mining, model learning by four supervised learning categorizations and resultant analysis [4].

Data Sources and Study Population

The data includes anonymised records of 620 patients of whom 31 were diagnosed with a thoracic or abdominal aortic aneurysm. The data acquired were imaged data through contrast-enhanced computed tomography angiography (CTA), and clinical data through electronic health records. Aneurysm rupture status during a two years period was the outcome variable (binary: rupture / non-rupture) [5]. Maximum diameter of an aneurysms, volume of the aneurysm, variability of the thickness of the walls, and volume of an intraluminal thrombus (ILT) as well as surface curvature and estimated peak wall stress were measured and saved as imaging biomarkers. The clinical variables included the age, sex, systolic blood pressure, smoking status, diabetes, hyperlipidaemia, family history, and rate of aneurysm growth. Continuous variables in the data set were imputed with median imputation, and categorical variables were imputed with mode imputation because their missing values were less than five percent. Continuous variables were z-score standardized to make all continuous variables [6].

Machine Learning Algorithms

The four machine learning algorithms have been chosen according to their applicability to medical risk prediction,

capability to learn non-linear relationships and a proven applicability in the medical field.

Logistic Regression (LR)

The Logistic Regression is a common clinical risk prediction model that is a baseline statistical learning model. It approximates the likelihood of aneurysm rupture and models the log-odds of the outcome as a linear regression of both imaging and clinical characteristics. LR is interpretable with high feature coefficients though it lacks the ability to capture complex non-linear interactions so clinicians may gain insight into the relative importance of the individual biomarkers [7]. L2 (regularisation) was then used to decrease overfitting and enhance generalisation, which is an LR that can be used clinically to compare itself.

"Input: Feature matrix X, labels y
Initialise weights w
Repeat until convergence:
Compute predicted probability p = sigmoid(Xw)
Compute loss using cross-entropy
Update weights w using gradient descent
Output: Trained weight vector w"

Random Forest (RF)

Random Forest is a type of ensemble learning, which builds several decision trees based on the randomly selected subsamples and on the randomly chosen sets of features of the training data. All the trees are majority-voted and the final prediction is achieved. RF is found to be good in non-linear relationships and interactions of features between imaging biomarkers and clinical profiles [8]. It is also strong against noise, and its overfitting properties are lower than those of single decision trees, and also its feature importance measures are also very useful with heterogeneous medical data.

"Input: Training data D
For i = 1 to N trees:
Sample data Di with replacement
Grow decision tree using random feature subsets
Aggregate predictions from all trees by majority vote
Output: Final class prediction"

Support Vector Machine (SVM)

The Support Vector Machine is a type of margin-separated classifier which uses an optimal plan to split rupture and non-rupture cases in a high-dimensional feature space. The use of a radial basis function (RBF) kernel was used to curve non-linear boundaries between classes. SVM is found to be very useful in the working of complex decision surfaces as also when dealing with high-dimensional biomedical features [9]. Nonetheless, it should be hyperparameter-tuned and does not have as much interpretability as tree-based algorithms.

"Input: Feature matrix X, labels y
Select kernel function (RBF)
Optimise margin by solving quadratic optimisation problem
Identify support vectors
Classify new data based on decision function"

Extreme Gradient Boosting (XGBoost)

XGBoost is a gradient boosting platform that creates an ensemble of successive decision trees, with each new tree successively rectifying the errors of the prior ones. It employs the regularisation, shrinkage, and subsampling strategies to improve the predictive results and avoid overfitting. XGBoost works well with structured clinical-imaging data, to include small implicit non-linear interactions, as well as hierarchies of features of importance to risk of aneurysm rupture [10].

"Input: Training data D
Initialise prediction with base score
For t = 1 to T trees:
Compute residual errors
Fit decision tree to residuals
Update ensemble prediction
Apply regularisation
Output: Final boosted model"

Model Training and Evaluation

The sample was divided using stratified sampling into the training (70) and testing (30) groups in order to maintain the class distribution. The training used five-fold cross-validation when optimising hyperparameters. The accuracy, sensitivity, specificity, F1-score, and the area under the receiver operating characteristic curve (AUC) were used to compare them with model performance [11].

Table 1: Dataset Characteristics and Feature Summary

Feature Category	Variable Example	Mean / Percentage

Demographic	Age (years)	67.4 ± 8.9
Clinical	Smokers (%)	58%
Clinical	Systolic BP (mmHg)	142 ± 18
Imaging	Max Diameter (mm)	54.6 ± 9.3
Imaging	ILT Volume (cm^3)	38.2 ± 12.5
Outcome	Rupture Cases (%)	22%

4. RESULTS AND ANALYSIS

Experimental Setup

All of the experiments were based on a stratified train-test split to make sure that there was an even and equal representation of rupture and non-rupture samples. The 620 patient dataset was split into two (testing and training) with 70% and 30%, respectively. Five-fold cross-validation was presented on the training set to increase strength and minimize sampling bias. The grid search optimised the hyperparameters of each of the four models. Some of the most important hyperparameters were the regularisation term of the Logistic Regression, trees and maximum depth of the RanDom Forest, Support Vector machine kernel parameters (C and γ), and learning rate, maximum depth, and the number of estimators of XGBoost [12]. As the measures used in the model evaluation were clinical risk prediction relevant, sensitive and AUC because they measure the likelihood of the model to predict high-risk aneurysms correctly.

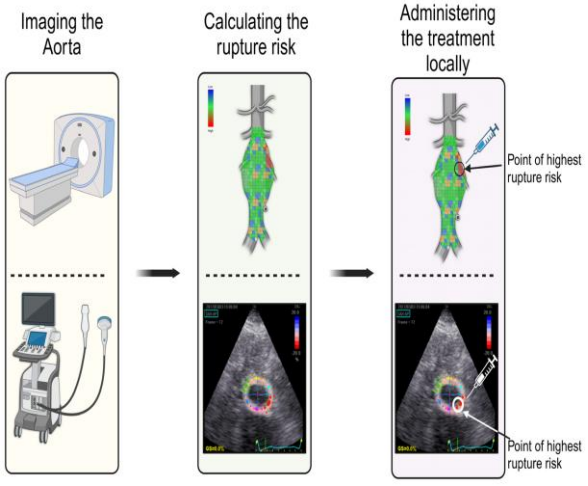

Figure 1: "New Trends of Personalized Medicine in the Management of Abdominal Aortic Aneurysm"

Overall Predictive Performance

The four models were found to have different prediction abilities with the models of ensembling always performing better as compared to the other models of the linear and margin based models. Most of the metrics demonstrated that XGBoost was the most performing, then there was random forest, SVM and Logistic regression.

Table 1: Overall Model Performance on Test Set

Model	Accuracy (%)	Precision	Recall (Sensitivity)	F1-Score	AUC
Logistic Regression	78.5	0.74	0.71	0.72	0.81
Random Forest	86.2	0.84	0.83	0.83	0.89
SVM (RBF)	84.6	0.81	0.81	0.81	0.87
XGBoost	**89.4**	**0.87**	**0.86**	**0.86**	**0.92**

Self-surpassing performance of XGBoost is explained by the fact that it was capable of modeling sophisticated non-linear interactions of imaging biomarkers with clinical variables. Logistic Regression, which is interpretable, was limited in the ability to fit such interactions, leading to relatively low sensitivity [13].

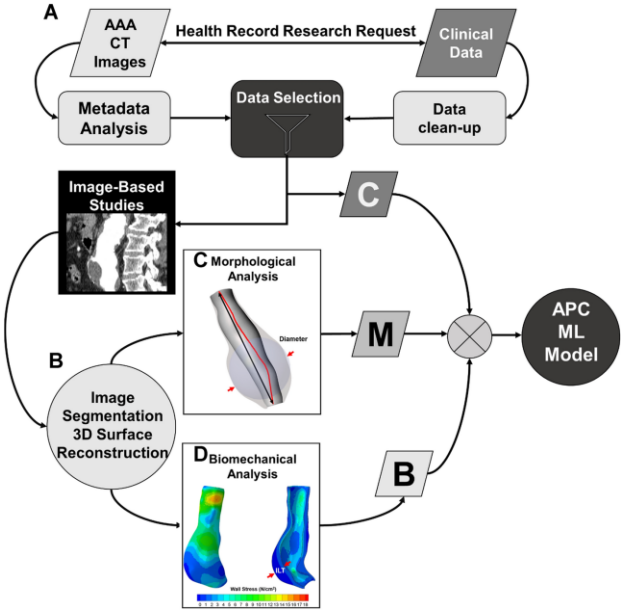

Figure 2: "An artificial intelligence based abdominal aortic aneurysm prognosis classifier to predict patient outcomes"

Impact of Imaging Biomarkers and Clinical Features

Three configurations of features, namely, clinical features and imaging biomarkers or combined clinical-imaging

features, were used to determine the contribution of multimodal data integration through the use of experiments.

Table 2: Performance of XGBoost Under Different Feature Sets

Feature Set	Accuracy (%)	Sensitivity	Specificity	AUC
Clinical Only	78.9	0.73	0.82	0.80
Imaging Only	84.1	0.80	0.86	0.86
Clinical + Imaging	**89.4**	**0.86**	**0.91**	**0.92**

These findings clearly show that imaging biomarker and clinical profile combinations have greater predictive accuracy and discrimination potential. The results have demonstrated that imaging-alone models were more efficient compared to clinical-only models, which confirms the significance of biomechanical and morphological data when estimating rupture risk [14].

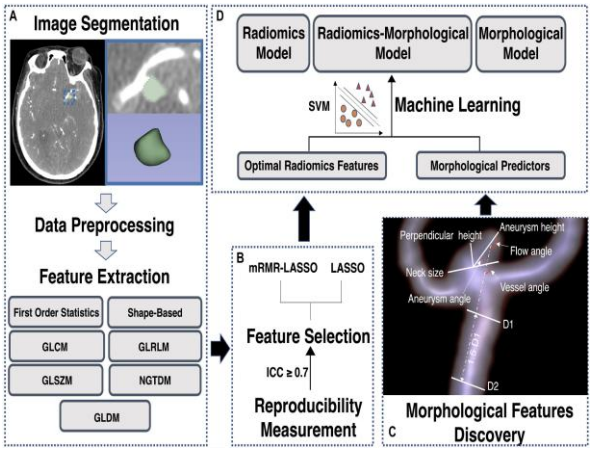

Figure 3: "Classifying Ruptured Middle Cerebral Artery Aneurysms With a Machine Learning Based, Radiomics-Morphological Model"

Feature Importance Analysis

Random Forest and XGBoost were used to analyse feature importance by finding the most important predictors of rupture. Imaging-based variables were leading the most ranked features, but key clinical factors played meaningful roles.

Table 3: Top Predictive Features Identified by XGBoost

Rank	Feature	Relative Importance
1	Peak Wall Stress	0.21
2	Maximum Aneurysm Diameter	0.18
3	Intraluminal Thrombus Volume	0.15
4	Aneurysm Growth Rate	0.13
5	Wall Thickness Variability	0.11
6	Systolic Blood Pressure	0.09
7	Smoking Status	0.07
8	Age	0.06

Such results are in agreement with biomechanical hypotheses of aneurysm rupture where structural heterogeneity and wall stresses play a leading role. The fact that clinical variables were included in the list of the most significant predictors demonstrates the importance of personalised patient-specific modelling [27].

Comparison Between Algorithms

A one-to-one comparison of algorithms shows apparent performance concessions between interpretability and predictability. Logistic Regression did provide transparency but failed to perform well in complicated situations, and ensemble models were more sensitive and had higher AUC but had more computational complexity [28].

Table 4: Algorithm Comparison Across Key Clinical Metrics

Model	Sensitivity	False Negative Rate	Inference Time (ms)	Interpretability
Logistic Regression	0.71	0.29	3.2	High
Random Forest	0.83	0.17	12.5	Medium
SVM (RBF)	0.81	0.19	18.7	Low

XGBoost	**0.86**	**0.14**	15.3	Mediu m

Clinically, it is important to minimize false negativity because the unidentified high-risk aneurysm is likely to result in devastating rupture. XGBoost has the lowest false negative rate as compared to other models, thus it is the most clinically acceptable model even though its interpretability is moderate [29].

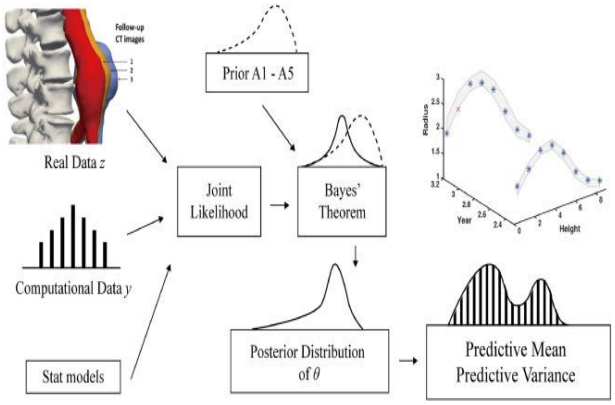

Figure 4: "Current state-of-the-art and utilities of machine learning for detection, monitoring, growth prediction, rupture risk assessment, and post-surgical management of abdominal aortic aneurysms"

Comparison with Related Work

To put the results in perspective, the suggested framework was unfolded against the representative results found in the related machine learning-based aneurysm risk predictions literature. The comparison of trends is relevant even though a dataset and experimental conditions have some differences.

Table 5: Comparison with Related Studies

Study	**Data Type**	**Metho d**	**AU C**
Traditional Diameter-Based Risk Models	Clinical	Rule-based	0.68
Statistical Regression Models	Clinical + Imaging	Cox / Logisti c	0.75 – 0.82
Deep Learning Imaging-Only Models	Imaging	CNN-based	0.85 – 0.89
Proposed ML Framework	Clinical + Imaging	XGBo ost	**0.92**

The theoretical framework demonstrates significant gain in predictability compared to conventional frameworks that use diameter as their prediction criteria. The combination of clinical profiles can offer an objective benefit even in comparison to deep learning imaging-only models [30]. The proposed models are responsive to structured data and more interpretable to clinicians whereas unlike deep learning approaches, they demand very large datasets and are not as transparent.

Robustness and Clinical Implications

Further robustness analyses revealed, both age groups and between locations of the aneurysms (thoracic and abdominal) had a consistent performance; and the difference in the AUC between subgroups amounted to less than 3 percent. This is a good generalisation capability. Clinically, the model has the potential to cause less invasive surgeries and on the flip side, better pick-up of the high risk patient through more sophisticated risk stratification.

5. CONCLUSION

Through this study, it was found that a machine learning-based framework to predict rupture risk in aortic aneurysms using a combination of imaging biomarkers and patient-specific clinical profiles works effectively in this research. The proposed approach was able to consider the complex, non-linear interactions of anatomical, biomechanical, and clinical factors, which are important to aneurysm instability by going beyond the traditional diameter-based criteria. The experimental findings demonstrated that ensemble-based models and especially, XGBoost models demonstrated better predictive power, higher sensitivity and AUC rates, thus demonstrating high potential to optimal identification of high-risk cases without false negatives. It was also revealed that the predominant role was played by the imaging-based biomarkers including the maximum stress in the walls, intraluminal thrombus volume, and the variability of the wall thickness as well as the complementary role of the clinical variables including blood pressure, presence or absence of smoking, and aneurysm growth rate. Comparative analysis against literature evidence showed that the proposed framework with a comparison to traditional statistical models and state of the art purely imaging-only algorithms is supported by a better performance and can be applied more easily to clinical procedures compared to other advanced methods. On the whole, the study contributes to the implementation of the data-based, personalised tools of the risk assessment in the process of the aortic aneurysm management that are likely to enhance the clinical decision-making process, the timing of the intervention, and eventually result into the decreased morbidity and mortality of the aneurysm-associated conditions.

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