

An Interpretable Machine Learning Framework for Early Prediction of Febrile Seizure Risk in Children

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Abstract:

Background: Febrile seizures are the most frequent cause of convulsive disorder during childhood and still represent a great discomfort for the patients' families and also for the treating physician. Although most cases have a benign course, clinical value of finding the children with higher risk in advance is nonetheless favorable for low resources or real-time monitoring.

Objective: This research work was designed to create a predictive model of early onset of febrile seizures with clinically interpretable predictions, low computational cost, and with the strict focus on embedded-system implementation and the resulting data visualization to gain more clinical understanding.

Methods: Monte Carlo simulation was used to obtain a synthetic dataset of 1,000 cases of pediatrics subject to aggregated epidemiologic statistics of a published clinical study. Predictor variables were age, sex, body temperature, family history of febrile seizures and maternal smoking during pregnancy. A stratified 70/30 train test split was used to train a logistic regression model. The accuracy of classification, receiver operating characteristic (ROC) analysis, and odds ratios with corresponding confidence intervals were used to assess model performance. The last model took the form of a closed-form mathematical equation that can be employed using low-power embedded systems.

Results: The proposed model had a classification accuracy of 83.67% and area under ROC curve (AUC) of around 0.90. Family history of febrile seizures was found to be the most powerful predictor (OR > 8), then high body temperature and maternal smoking in pregnancy. Visual inspection indicated that there were clear distributions patterns in the seizure and non-seizure groups in all the predictors. The resulting equation was numerically stable and of low computational complexity and can be implemented in real-time on resource-constrained machines.

Conclusions: Clinically meaningful prediction of Febrile seizure prediction can be done with a small number of variables easily available and with clinically meaningful prediction. The suggested framework is feasible as it offers a viable base of interpretable, entrenched clinical choice-support frameworks and presents a scalable path toward validation of the same with genuine clinical data in the future. The visual analytics help to improve clinical knowledge of risk factor distributions and interactions.

Keywords: Febrile Seizures, Embedded Healthcare Systems, Pediatric Risk Prediction, Clinical Decision Support Systems.

I. INTRODUCTION

Febrile seizures are the most common seizure disorder among children below age five years, with the prevalence of the condition ranging between 2-5 percent of children in the pediatric population of the population globally [1-3]. Despite generally being self-limiting, febrile seizures are linked with significant parental distress, ED visits, and, in a subgroup of patients, a high probability of reoccurrence or subsequent epilepsy. It is difficult to diagnose children who are at high risk early, especially in areas where no sophisticated laboratory tests are available or where no neuroimaging can be used [4, 5].

Recent developments in machine learning have shown potential in risk stratification of pediatric patients, although most of the current models assume high-dimensional data, or intricate architectures, or black-box algorithms that make them less interpretable and unable to be deployed in the real world. Also, dynamic visual analytics are not present in many studies to improve clinical insight into the interaction of various risk factors and their distribution in groups of patients. Conversely, clinical decision-support systems to be used by many users, particularly in low resource settings, should be calibrated to achieve performance in predicting and transparency, robustness, computational efficiency, and visual interpretability [6, 7].

This gap has been filled by the current research that suggests a predictive framework to estimate the likelihood of febrile seizure that is interpretable and lightweight. With the help of epidemiologically constrained synthetic data, logistic regression model and extensive visual analytics, we will prove that predicting risks with considerable reliability is possible with a minimum of routinely measured clinical variables, and that the system can still be used by embedded medical systems, as well as offer better clinical information via intuitive visualizations [8, 9].

II. Related Work

Kubota et al. (2021) [10] examined body temperature as a predictor of febrile seizure recurrence in the same febrile disease. Their cohort study has shown that peak body temperatures were directly linked to the risk of epileptic seizures even with other demographic variables held constant. This paper highlighted that it is not infection fever itself but the severity of the fever that is a critical predictor of seizure vulnerability, which justifies the importance of accurate temperature regulation in children.

Castellazzi et al. (2024) [11] performed a 10-year retrospective cohort study that investigated the clinical and laboratory-based parameters related to early febrile seizure recurrence. Their results indicated that the age at onset, optimal temperature, and chosen laboratory markers had a strong effect on recurrence during the first 24 hours. The authors emphasized that the combination of fundamental laboratory markers and clinical variables is good at the early detection of risks without the need of complex testing.

Shen et al. (2024)[12] examined predictors of febrile seizure recurrence in a large cohort of pediatric patients through retrospective cohort designs. They confirmed their results that younger age, family history of febrile seizures, and high body temperature were independent risk factors. The research supported the idea that clinical variables that can be obtained regularly can predict accurately risk of seizures in children, especially in repeated situations.

Yalçın et al. (2025) [13] have provided a prospective cohort study with a combination of clinical, biochemical and genetic assessments in children having febrile seizures. The researchers found the disturbance of electrolytes, micronutrients deficiencies, and pathogenic genetic variants as the reasons that contributed to a higher risk of seizures, especially in complicated and frequent cases. Although the range of studied variables was large, the study proved that traditional clinical parameters are at the core of risk stratification, and biochemical and genetic variables are considered amplifiers, not independent predictors.

Papež et al. [14] suggested a multivariate linear mixture model to identify the likelihood of febrile seizures and their recurrence. They incorporated both demographic and laboratory

variables in their approach with a predictable statistical model that could be interpreted better than the univariate models. The paper emphasized the value of transparency and clinical interpretability, which enabled clinicians to personally evaluate the value of each individual predictor.

Cheng et al. [15] created and studied a predictive model of febrile seizures with regularized regression methods. Their model resulted in a powerful discrimination by incorporating demographic and laboratory capabilities, but still being simple and clinically usable. The authors pointed out that a well-chosen set of features might be able to provide high predictive power without the need to use sophisticated machine-learning structures.

Salim et al. (2025) [16] used non-clinical areas have also shown that machine-learning methods are effective in model complex resource constrained systems. lightweight machine-learning models to make predictions of packet loss in wireless sensor networks, and demonstrated that predictive performance based on a carefully chosen set of feature usage and computationally efficient algorithms could have the meaning of prediction. Though in a networking environment, it demonstrates the general applicability of interpretable machine-learning models to real-time decision-making in systems with noisy data, limited resources and operational constraints- which is also applicable directly to the embedded healthcare monitoring uses.

Doshi-Velez and Kim (2017) [17] discussed the more general issue of interpretability of machine-learning models used to make high-stakes medical decisions. They claimed that transparency deficiency in black-box models constrains clinical trust and practiceability especially in the context of application in pediatrics where explainability is essential. Their effort was the theoretical basis of preference to interpretable models of risk prediction in clinical settings.

Rudin (2019) [18] also reaffirmed the same view by proposing the utilization of inherently interpretable models instead of post-hoc explanation of black-box systems in the medical practice. This paper has underscored the importance of interpretability in safety, accountability, and regulatory acceptance in particular in the case of decision-support systems that involve vulnerable populations such as children.

Halimeh et al. (2023) [19] assessed the explainable artificial intelligence approaches to wearable seizure monitoring and showed that the quality of data, age of a patient, and the reliability of physiological signals play a significant role in determining the performance of a model. Their results demonstrated that significant feature choice as well as sound data gathering can easily override algorithm complexity in wearable seizure awareness systems.

Ramgopal et al. (2023) [20] conducted a review of artificial intelligence-driven clinical decision-support systems in pediatrics and came to the conclusion that models that should be deployed in real-time should balance between accuracy, interpretability, and computational efficiency. In the research, it was highlighted that clear models which are easily understood and evaluated by clinicians are especially useful in pediatrics.

Dosani et al. (2009) [21] performed a clinical assessment of context-sensitive physiological monitoring algorithms in children. Their findings showed that physiologically-based qualities

and prudent system design are key to dependable performance and prove the idea that well-structured and simple models are effective indeed under pediatric monitoring conditions.

III. Methods

A. Study Design and Data Source

This work adopted a computational modeling and simulation-based design with integrated visual analytics. No individual-level patient data were used. Instead, synthetic data were generated based on aggregated demographic and clinical statistics reported in a previously published peer-reviewed clinical study [6]. These statistics described key characteristics of pediatric patients with febrile seizures and febrile controls without seizures.

Table 2 [13] , reports demographic and clinical characteristics of pediatric patients with febrile seizures and febrile controls without seizures, including age, gender distribution, body temperature, family history of febrile seizures, and maternal smoking during pregnancy. These aggregated statistics served as the reference distributions for the synthetic data generation [6].

B. Synthetic Dataset Generation

In this study, MATLAB R2023a (MathWorks) was used for all statistical analyses, model development, and user interface. A total of 1,000 synthetic pediatric samples were generated using Monte Carlo simulation. Each synthetic case represented a hypothetical child characterized by five predictor variables and one binary outcome variable indicating febrile seizure occurrence.

The simulation process was limited to recreate the published epidemiological distributions of each variable, which is with clinically significant differences in seizure and non-seizure groups. This methodology allowed the researcher to obtain realistic inter-variable correlations and control the quality and distribution properties of the data.

C. Variables and Clinical Ranges

The dataset included the following variables (Table 1):

TABLE 1. Dataset Variables and Descriptions

Variable	Type	Range/Values	Description	Coding/Notes
Age	Continuous	6 – 60 months	Age of the child in months at the time of assessment	-
Sex	Binary	0 or 1	Biological sex of the child	0 = Female 1 = Male
Body Temperature	Continuous	37.0 – 41.0 °C	Measured body temperature during febrile episode	-
Family History of FS	Binary	0 or 1	Indicates whether there is a family history of febrile seizures	0 = No 1 = Yes

Maternal Smoking	Binary	0 or 1	Indicates maternal smoking during pregnancy	0 = No smoking 1 = Smoking during pregnancy
Febrile Seizure Outcome	Binary (Target)	0 or 1	Primary outcome variable indicating occurrence of febrile seizure	0 = No seizure 1 = Seizure occurred

Note: FS = Febrile Seizures

D. Statistical Distributions Predictive Model Development

Binary variables were generated using Bernoulli distributions with probabilities that matched the values reported in the reference study [13]. The body temperature was modelled using standard deviations and means of group-specific Gaussian distributions around the means of the seizure and non-seizure cohorts. The age selection was taken on a uniform distribution within clinically realistic pediatric boundaries. Separate sets of parameters were used in the seizure and control groups to maintain inter-group contrasts.

A logistic regression model was developed to predict the probability of occurrence of febrile seizure based on five clinical predictors. The logistic regression model was chosen because it is widely accepted in clinical studies, directly interpretable in terms of odds ratio, stable, and has low computational complexity. The model expresses the probability of seizure as a logistic regression of a linear expression of predictors with coefficients obtained during training. This formulation enables direct translation into a closed form equation (Eq. 1) suitable for implementation in C/C++ on embedded hardware.

$$P(FS) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}} \quad (1)$$

where β_0 is the intercept and $\beta_1 - \beta_5$ are the regression coefficients learned from the data.

E. Visual Analytics Framework

A comprehensive visual analytics framework was adopted to facilitate critical clinical interpretability and to give more insightful information on the data structure and model behavior. This framework included:

- a) Feature Correlation Heatmap: Visual representation of inter-variable relationships using color gradients to illustrate correlation strength and direction.
- b) Detailed Correlation Matrix: Numerical display of correlation coefficients with color coding for rapid pattern recognition.
- c) Distribution Visualizations: Comparative analyses of variable distributions between seizure and non-seizure groups, including:
 - [1]. Gender distribution by FS status
 - [2]. Temperature distribution by FS status
 - [3]. Age distribution by FS status
 - [4]. Family history distribution by FS status
 - [5]. Smoking exposure distribution by FS status

F. Model Training and Validation

Stratified sampling was used to create a synthetic dataset to balance the classes and split it randomly into training (70%) and testing (30%) data subsets. Classification accuracy and ROC analysis were used as the model performance measures. The regression coefficients were converted to odds ratios and 95% confidence intervals to measure the relative contribution of each of the predictors. The visual analytics were used on the training dataset and test dataset to be consistent in patterns.

IV. Results

I.Characteristics of the Synthetic Dataset

The dataset produced maintained the epidemiological patterns in the literature used. Febrile seizure group children showed more prevalence in the positive family history and high peak body temperatures than controls. The exposure to maternal smoking was also higher in the group of seizures, whereas age and sex were largely similar, Table 2.

TABLE 2 Characteristics of the Synthetic Dataset by Outcome Group

Variable	Non-Febrile Seizure Group	Febrile Seizure Group
Age (months)	6–60	6–48
Male gender (%)	~61%	~57%
Temperature (°C)	37.0–40.2	38.0–41.0
Family history of FS (%)	~9%	~67%
Maternal smoking (%)	~13%	~37%

Note: Values are derived from synthetic data constrained by published epidemiological statistics [13].

II.Model Performance

On the independent test, the logistic regression model had a classification of 83.67% and an AUC of about 0.90 (Fig. 1). The ROC curve showed high levels of discrimination between the cases of seizure and non-seizure, suggesting good balance between sensitivity and specificity, although the number of predictors was low. The visual analytics model improved the model interpretability, that is, a descriptive explanation of the predictive patterns of the model.

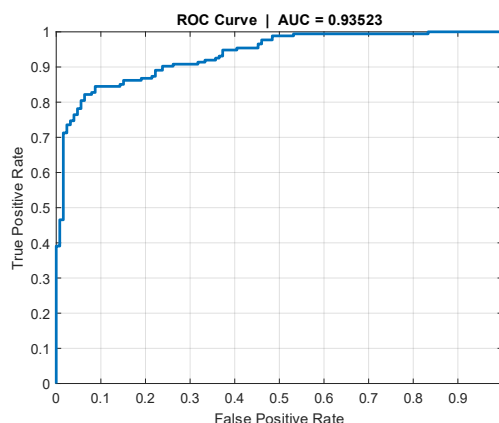


Fig 1. Receiver Operating Characteristic (ROC) curve.

III. Visual Analytics Results

In order to improve the clinical interpretability and to gain a better understanding of the interactions between risk factors, full-fledged visual analytics were introduced: The complicated relations between clinical variables in predicting febrile seizure risk are presented in Fig. 2 (Feature Correlation Heatmap). The heatmap reveals the strongest positive relationship with seizure occurrence was the heatmap, which supports the central role of the heatmap in the pathophysiology of seizures. There is a great significance of family history implying the genetic part of the seizure susceptibility. Surprisingly, the visualization indicates that there is a small amount of correlation between gender and susceptibility to seizures, and it disproves popular clinical beliefs regarding the variability in susceptibility between the genders.

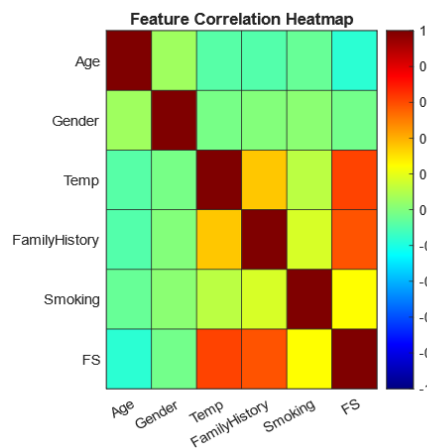


Fig 2. Feature Correlation Heatmap.

The Detailed Correlation Matrix (Fig. 3) has given a quantitative validation of the relationships seen in heatmap. The matrix validates a 0.62 degree of association between temperature and the presence of seizures, which is the strongest independent predictor. The correlation coefficient between family history and smoking exposure is 0.58 and that between smoking exposure and family history is moderate (0.25). The adverse relationship between age and the risk of seizures (-0.17) is graphically validating the established clinical observation that younger children are at a more risk.

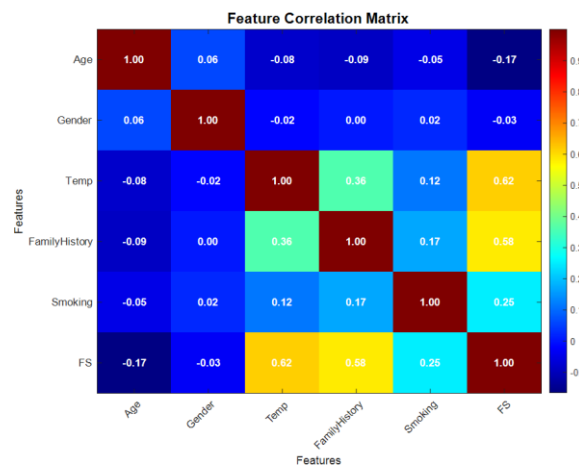


Fig 3. Detailed Correlation Matrix.

Fig. 4 (Gender Distribution by FS Status) captures a sensitive image of the variations in gender distribution in the seizure and non-seizure groups. Although the bar chart is suggesting apparent results in distribution (62.6% of FS positive and 37.4% of FS negative), the correlation matrix reminds us that gender presents minimal direct correlation when other factors are held constant. Although this visualisation is a valuable clinical lesson that apparent patterns in simple distributions need not be the result of direct causal relationships, there could be confounding variables.

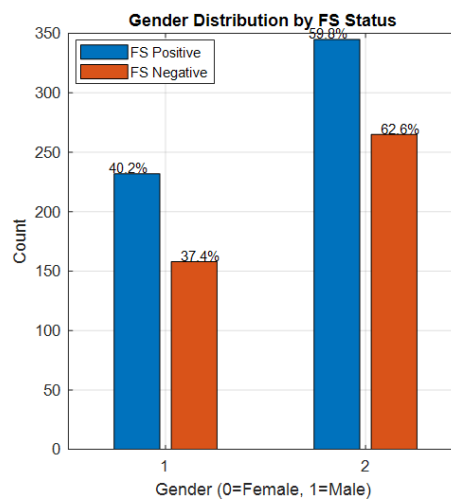


Fig 4. Gender Distribution by FS Status.

Fig. 5 (Temperature Distribution by FS Status) provides compelling visual evidence of the temperature-seizure relationship. The overlapping histograms indicate obviously that FS-positive cases are concentrated at higher temperatures (peak at 38.9°C) and FS-negative at lower temperatures (peak at 38.2°C). The 38°C vertical line successfully isolates the two distributions, confirming this as a threshold that is clinically significant. The critical zone range of 38-39°C of decision is the area of overlap where there are other determining factors of risk.

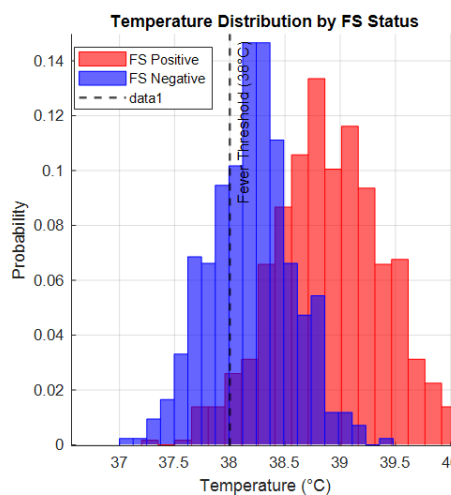


Fig 5. Temperature Distribution by FS Status.

The developmental window of vulnerability is proved graphically in Fig. 6 (Age Distribution by FS Status). Box plot depicts that FS-positive children are concentrated around younger age groups (6-48 months) with a narrow interquartile range whereas FS-negative cases represent the wider age range with older children. The visualization is communicative in explaining the importance of the 6-36-month window of seizure prevention and monitoring by pediatricians.

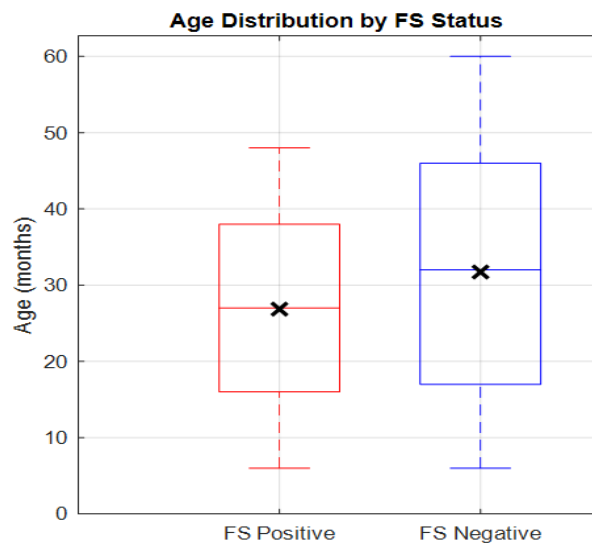


Fig 6. Age Distribution by FS Status.

Fig. 7 (Family History Distribution by FS Status) demonstrates the sharp difference in the risk factors of heredity between groups. This binary distribution pattern confirms that family history is a very powerful categorical predictor dramatically changing the risk calculations. This illustration can be used to reinforce the clinical practice of comprehensive family history taking, demonstrating that this simple yes/no question contains strong predictive data.

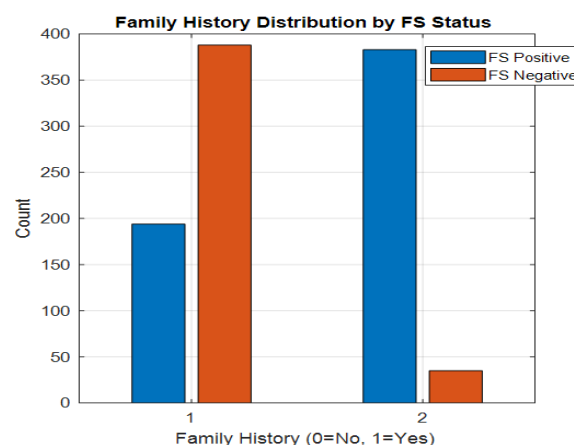


Fig 7. Family History Distribution by FS Status.

Fig. 8 (Smoking Exposure Distribution by FS Status) demonstrates the environmental factors on the risk of seizures. The prevalence of smoking exposure during the seizure group is also

more common than the control group, which supports the idea of environmental factors as risk amplifiers. The visualization is significant regarding the implications of the study on public health, as it hints that the reduction of smoking in the household may be a preventative measure that can be manipulated. Reducing the risk of seizures.

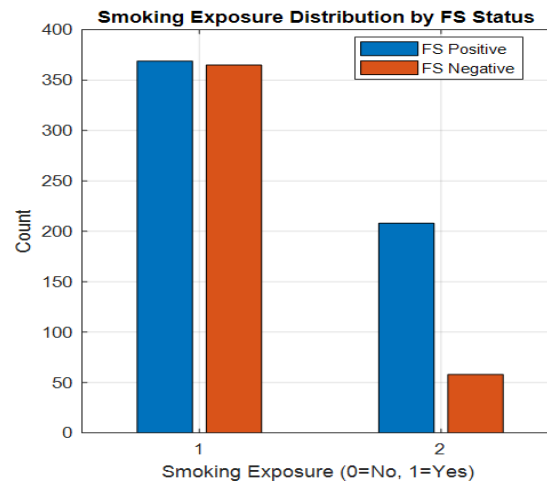


Fig 8. Smoking Exposure Distribution by FS Status.

IV. Clinical Decision Support Interface

The predictive model presented in Fig. 9 is practically implemented to demonstrate the integrated graphical user interface (GUI) that has been designed in the febrile seizure clinical decision support system. The interface was worked out to be:

- (1) Clinically User-Friendly: Allows easy input of the five clinical variables (age, gender, temperature, family history, smoking exposure).
- (2) Provides Immediate Results: Displays prediction outcome (33.02% in this example) with risk level classification (Medium).
- (3) Offers Practical Recommendations: Automatically generates a medical report and customized recommendations based on risk level.
- (4) Ensures Transparency: Displays the logistic regression equation used in calculations, allowing clinicians to understand the mathematical basis of predictions.
- (5) Supports Embedded Applications: Provides the equation in a format directly executable on Arduino and embedded systems.

The Example Shown: A 24-month-old female with temperature 38.5°C, no family history of seizures, and no smoking exposure, receives a risk estimate of 33.02% classified as "Medium" level, warranting close monitoring and temperature measurement every 2 hours.

This interface is a connection between the complicated statistical paradigm and its implementation into actual clinical use to translate mathematical equations into clinical action.

Fig 9. Clinical Decision Support Interface.

V. Risk Factor Analysis

Table 3 reveals that a family history of febrile seizures is most strongly correlated with seizure occurrence, which is later closely followed by increased body temperature and maternal smoking during prenatal life. There was a modest relation with male gender and a weak anti-relationship with age, which is in line with well-reported age-related predisposition patterns [12, 22]. These statistical findings were complemented by visual analytics that were used to outline the distribution of these factors between risk groups.

Table 3. Odds ratios for febrile seizure predictors

Predictor	Odds Ratio (OR)	95% CI
Age	< 1.0	Narrow
Gender (Male)	~1.1	Moderate
Temperature	> 2.0	Significant
Family history	> 8.0	Strong
Maternal smoking	> 3.0	Significant

V. Discussion

This paper illustrates that substantial predictive accuracy of febrile-seizure risk is attainable with a simplified, clinically intuitivist system of covariates, with additional extensive visual analytics that permit more in-depth information about risk factor distributions and interactions. The dominance of family history as a risk factor (Table 3) is consistent with universally extensive evidence of a genetic role in febrile-seizure vulnerability. This relationship is immediately easily read by the visual distribution plots (Figs. 7-8), which show stark differences between the groups in the family-histories prevalence.

Equally, the robust correlation with fever severity, supported by the temperature-distribution graph (Fig.5), demonstrates the significance of the magnitude of temperature, but not necessarily the occurrence of fever itself. The distinct division of the distributions around 38 C-degrees provides the visual confirmation of the given clinical threshold whereas the area in between serves to remind clinicians that temperature is not enough to determine the risks unequivocally.

Pregnancy maternal smoking was also found to be a predictive variable, and the distribution plot (Fig. 8) shows clear-cut differences between groups. This result supports previous reports that reported prenatal environmental exposures to be modifications of neuro-developmental exposure vulnerability and is shown graphically that can be used to educate patients about their risk factors which are modifiable.

The age-distribution visualization (Fig. 6) is a good message that can convey the risk window of the development and explain why the preventive attention of pediatricians is concentrated on children under 36 months. Susceptibility patterns according to age will be statistically apparent in practice, and the small box to FS-positive cases and the larger to FS-negative cases visually substantiates the patterns of the susceptibility.

Gender-distribution analysis (Fig.4) that is taken into account, supplemented by the correlation matrix (Fig.3), provides a rather crucial methodological lesson: even the differences in distribution, which might appear quite simple, may be rather deceptive without getting to confounding variables. This figure explains why gender has little predictive value in multivariate analysis despite the expected distribution variations.

Engineering The clinical decision- support interface (Fig. 9) facilitates transparent decision-making and embedded implementation. In contrast to black-box models, the available framework allows clinicians and engineers to examine the risk contributions individually, by which case, trust and regulatory compliance is guaranteed in biomedical applications. This openness is enhanced by the visual-analytics component, which makes complex statistical linkages easy to understand in a manner that is intuitively easy to interpret.

Despite the lower performance than the performance that has been obtained in research using laboratory or neuro-imaging biomarkers, the model proposed presents a viable trade-off between the accuracy, interpretation, visual comprehensibility, and deployability. Critically, the framework is extensible to offline optimization or hybrid modelization without compromising its integrated compatibility and visual interpretability [23, 24].

VI. Limitations

There are a number of limitations which are to be considered. First, synthetic data could fail to reflect all latent correlations found in clinical populations in the real world. Second, the predictor set was purposely reduced to ensure the simplicity and internalized feasibility, eliminating biochemical markers that are also known to enhance the predictive ability. Third, validation was conducted based on one train-test split, and further research should include cross-validation and additional clinical data. Fourth, though the visual analytics do increase interpretability, it is built on synthetic data and needs to be confirmed using actual clinical populations.

Lastly, the model does not give final diagnoses but estimates of risk probabilities that should be utilized as a decision-support tool and not as a diagnostic tool to be followed by itself. The visualizations are to be used to boost the understanding, but not to replace clinical expertise.

VII. CONCLUSION

The paper introduces a lightweight, transparent and deployable febrile seizure predictive framework, along with a comprehensive collection of visual analytics, resulting in improved clinical interpretation and understandability. The proposed method combines epidemiologically limited synthetic data with a logistic regression model with user-friendly visualization to achieve the best balance between clinical importance, interpretability, computation speed, and visualization. The visual analytics system provides a more comprehensive account to clinicians of the risk factor distributions and their interactions and therefore helps them bridge the conceptual gap of statistical modeling and clinical intuition. The final model can be deployed on embedded systems because it has a closed form expression that allows real time monitoring and early-warning applications. To the best of the knowledge of the external validation and with the progressive addition of features, this framework can promise scalable pediatric decision-support systems in both the high and the low-resource environments.

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REFERENCES

- [1] D. Laino, E. Mencaroni, S. J. I. j. o. e. r. Esposito, and p. health, "Management of pediatric febrile seizures," vol. 15, no. 10, p. 2232, 2018.
- [2] S. Shinnar and T. A. J. J. o. c. n. Glauser, "Febrile seizures," vol. 17, no. 1_suppl, pp. S44-S52, 2002.
- [3] V. Thadchanamoorthy and K. J. I. N. D. J. Dayasiri, "Review on febrile seizures in children," vol. 12, pp. 25-35, 2020.
- [4] A. T. Berg and S. J. E. Shinnar, "Complex febrile seizures," vol. 37, no. 2, pp. 126-133, 1996.
- [5] A. J. E. j. o. p. Fetveit, "Assessment of febrile seizures in children," vol. 167, no. 1, pp. 17-27, 2008.
- [6] A. K. Leung, K. L. Hon, and T. N. J. D. i. c. Leung, "Febrile seizures: an overview," vol. 7, p. 212536, 2018.
- [7] D. C. Hesdorffer *et al.*, "Distribution of febrile seizure duration and associations with development," vol. 70, no. 1, pp. 93-100, 2011.
- [8] A. Ferretti *et al.*, "Best practices for the management of febrile seizures in children," vol. 50, no. 1, p. 95, 2024.
- [9] E. J. J. N. m. Topol, "High-performance medicine: the convergence of human and artificial intelligence," vol. 25, no. 1, pp. 44-56, 2019.
- [10] J. Kubota *et al.*, "Body temperature predicts recurrent febrile seizures in the same febrile illness," vol. 43, no. 7, pp. 768-774, 2021.

- [11] M. L. Castellazzi, A. La Vecchia, M. Scali, C. Agostoni, G. Di Pietro, and G. P. J. F. i. P. Milani, "Clinical and laboratory parameters associated with febrile seizure recurrence within the first 24 h: a ten-year cohort study," vol. 12, p. 1373848, 2024.
- [12] F. Shen *et al.*, "Risk factors and predictors of recurrence of febrile seizures in children in Nantong, China: a retrospective cohort study," vol. 24, no. 1, p. 420, 2024.
- [13] G. Yalçın *et al.*, "A Comprehensive Perspective on Febrile Seizures in Children: A Prospective Cohort Study with Evaluation of Clinical, Laboratory, and Genetic Features," vol. 14, no. 22, p. 7918, 2025.
- [14] J. Papež *et al.*, "Multivariate linear mixture models for the prediction of febrile seizure risk and recurrence: a prospective case–control study," vol. 13, no. 1, p. 17372, 2023.
- [15] A. Cheng *et al.*, "Development and validation of a predictive model for febrile seizures," vol. 13, no. 1, p. 18779, 2023.
- [16] M. S. Salim, N. Sabri, A. A. R. J. E. A. S. Dheyab, and Technology, "Predicting WSN packet loss using machine learning: Applications in solid surroundings," vol. 9, no. 2, pp. 289-302, 2025.
- [17] F. Doshi-Velez and B. J. a. p. a. Kim, "Towards a rigorous science of interpretable machine learning," 2017.
- [18] C. J. N. m. i. Rudin, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," vol. 1, no. 5, pp. 206-215, 2019.
- [19] M. Halimeh, M. Jackson, S. Vieluf, T. Loddenkemper, and C. J. S. E. J. o. E. Meisel, "Explainable AI for wearable seizure logging: Impact of data quality, patient age, and antiseizure medication on performance," vol. 110, pp. 99-108, 2023.
- [20] S. Ramgopal, L. N. Sanchez-Pinto, C. M. Horvat, M. S. Carroll, Y. Luo, and T. A. J. P. r. Florin, "Artificial intelligence-based clinical decision support in pediatrics," vol. 93, no. 2, pp. 334-341, 2023.
- [21] M. Dosani *et al.*, "Clinical evaluation of algorithms for context-sensitive physiological monitoring in children," vol. 102, no. 5, pp. 686-691, 2009.
- [22] L. Forsgren, R. Sidenvall, H. K. S. BLOMQUIST, J. Heijbel, and L. J. A. P. Nyström, "Pre-and perinatal factors in febrile convulsions," vol. 80, no. 2, pp. 218-225, 1991.
- [23] Z. Zou, B. Chen, D. Xiao, F. Tang, and X. J. J. o. M. I. R. Li, "Accuracy of Machine Learning in Detecting Pediatric Epileptic Seizures: Systematic Review and Meta-Analysis," vol. 26, p. e55986, 2024.
- [24] G. Yücel, A. K. Arslan, B. Özgör, and S. J. B. P. O. Güngör, "Prediction of recurrent febrile seizures risk during the same febrile illness in children at a single tertiary centre in Türkiye," vol. 9, no. 1, p. e002908, 2025.