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A Methodological Study on Fetal Health Classification Using Optimized LightGBM with SMOTE and Optuna-Based Hyperparameter Optimization

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ABSTRACT Objective: Fetal health classification is of great clinical importance as it allows the early detection and management of fetal health problems during pregnancy.This study aims to enhance fetal health classification by integrating Light Gradient Boosting Machine (LightGBM), synthetic minority oversampling technique (SMOTE), and Optuna-based hyperparameter tuning. The goal is to improve classification accuracy, address class imbalance, and optimize model performance in predicting normal, suspicious, and pathological fetal health conditions. **Material and Methods:** The study utilized the University of California, Irvine "Cardiotocography Data Set" which contains 2.126 fetal cardiotocography (CTG) records classified into 3 categories. To handle class imbalance, SMOTE is applied. Various machine learning models (Stochastic Gradient Descent Classifier, Gradient Boosting, Decision Tree, Support Vector Machine, K-Nearest Neighbors, and LG) were compared, with LightGBM selected due to its efficiency in structured medical data processing. Optuna is used for hyperparameter tuning. The dataset was split into 80% training and 20% testing, and model performance was assessed using accuracy, precision, recall, and F1-score. **Results:** The optimized LightGBM+SMOTE+Optuna model achieved 99% accuracy, significantly outperforming the other classifiers. The recall and F1-score for the suspicious and pathological classes improved, reducing the misclassification rates. The confusion matrix confirmed a substantial decrease in errors, demonstrating the model's robustness and reliability. **Conclusion:** The proposed model successfully enhances fetal health classification accuracy by addressing class imbalance and optimizing hyperparameters. The integration of LightGBM, SMOTE, and Optuna improves model generalization, making it a valuable tool for fetal health assessment. Future studies could explore deep learning approaches to further refine classification performance and support clinical decision-making.

Keywords: Fetal monitoring; machine learning; pregnancy

Fetal health classification plays a crucial role in the early detection and management of complications during pregnancy, facilitating timely interventions that can reduce perinatal risks and promote fetal well-being.[1] Pregnancy-related complications remain a significant public health concern globally and, if left undiagnosed or mismanaged, may result in adverse outcomes, including fetal mortality. This issue is particularly pronounced in low- and middle-income countries, where limited access to healthcare services intensifies these risks.

In response to such global health challenges, the Sustainable Development Goals emphasize reducing neonatal mortality to 12 per 1.000 live births and under-5 mortality to 25 per 1000 live births by 2030. Achieving these targets relies heavily on the early diagnosis and accurate classification of fetal health problems. Cardiotocography (CTG) is a widely used non-invasive monitoring tool that provides valuable insights into fetal heart rate patterns and uterine contractions.[2] While CTG is instrumental in detecting fetal distress and preventing adverse outcomes such

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as preterm birth, its interpretation is often subjective and may vary between clinicians, potentially leading to inconsistencies in clinical decisions. Therefore, the development of systematic and reliable classification methods is essential to enhance the objectivity and accuracy of fetal health assessments.

In recent years, machine learning (ML) has emerged as a powerful tool in medical diagnostics, offering promising results in fetal health classification. For instance, Özbay et al. reported 96% accuracy using rule-based algorithms, while Sharma et al. achieved 96.21% accuracy with a random forest optimized through the Enhanced Binary Bat Algorithm. Jebadurai et al., Sulihati et al., and Mehbodniya et al. employed various feature selection and optimization techniques, achieving accuracies ranging from 91% to 92%.[3-7] Yashaswini et al. combined synthetic minority oversampling technique (SMOTE) and principal components analysis (PCA) with Random Forest, reaching 97.58% accuracy, and Sefidi et al. enhanced the Support Vector Machine (SVM) performance to 93.98% with a genetic algorithm.[8,9] These studies not only underscore the effectiveness of ML approaches but also highlight persistent challenges such as class imbalance and hyperparameter optimization.

The primary objective of this study was to develop an optimized ML framework that improves fetal health classification performance. We employed a Light Gradient Boosting Machine (LightGBM), recognized for its efficiency and scalability in processing large datasets. To address the class imbalance issue, we integrate the SMOTE, which enhances minority class representation, thereby mitigating model bias toward the majority class. Furthermore, Optuna, an advanced hyperparameter optimization framework, is used to fine-tune the model parameters, ensuring optimal performance. By combining LightGBM, SMOTE, and Optuna, this study aims to achieve superior classification accuracy, particularly in the challenging suspicious and pathological classes, and to enhance the model's generalizability and clinical utility. The proposed model offers the potential to enhance fetal health assessments by enabling real-time, automated decision-making, minimizing interobserver variability, and streamlining clinical workflows. These advancements align with global healthcare objectives aimed at improving maternal and fetal outcomes, particularly in resource-constrained environments.

MATERIAL AND METHODS

DATASET

This study used the "Cardiotocography Data Set" from University of California, Irvine for fetal health prediction.[12] The dataset comprises 2.126 records obtained from the cardiotocography (CTG) readings of pregnant women. The data were classified by 3 expert obstetricians, and a consensus classification process was conducted to ensure accuracy. Each record was categorized based on fetal health status into "Healthy", "Suspicious" and "Pathological". The dataset used in this study adheres to the ethical principles outlined in the Declaration of Helsinki. Specifically, the original data collection process ensured participant anonymity, confidentiality, and informed consent. No personally identifiable information was included, and the data were made publicly available for research purposes in accordance with ethical guidelines; therefore, the article does not need ethics committee approval.

OPTUNA PARAMETER OPTIMIZATION

Hyperparameter tuning is one of the most critical ML workflow steps. Selecting a set of optimal hyperparameters to improve a model's performance. Optuna is a practical and open-source hyperparameter optimization framework that automates the search for optimal hyperparameters. This framework aims to maximize the model performance by defining an objective function and searching for the best parameter combinations.[13] The optimization process works by accepting different hyperparameter combinations as input to maximize an objective function and output a validation score. The objective function dynamically describes the search space by interacting with the trial object. Optuna's efficient sampling method allows for processing both types of sampling.

MACHINE LEARNING CLASSIFICATION MODELS

In this study, 6 classifiers were used. Stochastic gradient descent (SGD) is an optimization algorithm commonly used in ML and deep learning to update model parameters based on gradient estimates iteratively, minimizing cost functions.[14] Unlike batch gradient descent, which computes the gradient over the entire dataset in each iteration, SGD updates the model parameters using a randomly selected data point per iteration. This stochastic approach reduces computational costs and trains large-scale models efficiently, making it particularly suitable for deep learning and large datasets.

Gradient Boosting (GB) is a powerful ensemble learning method that creates a strong predictive model by sequentially combining weak learners, typically decision trees (DTs), to minimize loss functions through gradient-based optimization.[15] Unlike traditional boosting methods such as AdaBoost, which assign weights to misclassified examples, GB optimizes a differentiable loss function using gradient descent at each stage.[16] In each iteration, a new tree fits the residual errors of the previous model, thereby reducing the bias and increasing the prediction accuracy.

DTs are supervised learning algorithms widely used for classification and regression tasks due to their interpretability, simplicity, and efficiency in handling numerical and categorical data. The fundamental idea behind DTs is to recursively split the feature space into subsets based on decision rules, forming a tree-like structure that represents the decision-making process.[17]

Logistic regression (LR) is a statistical and machine-learning technique commonly used for binary classification tasks where the target variable is categorical (Hosmer, Lemeshow, and Sturdivant).[18] Unlike linear regression, which assumes a continuous output, LR applies the logistic (sigmoid) function to model the probability of a given example belonging to a specific class.[18]

K-Nearest Neighbors (KNN) is a widely used classification and regression method because of its simplicity and effectiveness among supervised learning techniques.[19] The KNN typically uses different distance metrics such as the Euclidean distance, Manhattan distance, or Minkowski metric to identify the nearest neighbors.

LightGBM is a GB framework that significantly improves the efficiency and scalability of traditional Gradient Boosting Decision Trees (GBDT) by using histogram-based learning and leaf-wise growth strategies.[20] Unlike traditional GB methods, which split nodes level-wise, LightGBM adopts a leaf-wise growth approach that allows for deeper and more accurate splits while maintaining computational efficiency.

SAMPLE SIZE ADEQUACY AND POWER CONSIDERATIONS

While a formal power analysis is a standard approach in hypothesis-driven clinical studies to determine the necessary sample size for detecting statistically significant effects, ML studies-such as the present research-primarily focus on model performance metrics (e.g., accuracy, precision, recall, F1-score) rather than conventional hypothesis testing. Our study utilized the cardiotocography dataset comprising 2.126 samples, which is widely accepted and used in fetal health classification research and is considered sufficient according to prior literature.[3,4,7,10] To ensure the robustness and reliability of the classification results, we employed 10-fold cross-validation and reported comprehensive performance metrics, demonstrating that the sample size was adequate for effectively training and validating the ML models. This approach mitigates the risk of overfitting and enhances the generalizability of the findings. Therefore, we did not include a formal power analysis because it is not typically applicable in ML-based studies of this nature.

PROPOSED MODEL

In the proposed model, a 2-step feature selection process was applied to reduce the size of the dataset while retaining the most relevant and meaningful features, optimizing the performance of the ML models. This process removes unnecessary or redundant features from the dataset, allowing the model to produce more efficient and accurate results. In the first step, the fundamental features were identified and subjected to further analysis. In the second step, only the features that best supported the classification task were selected, enhancing the model's generalization ability. These selected features were then used in the subsequent stages to train and evaluate various ML models. As a result, this feature selection process op-

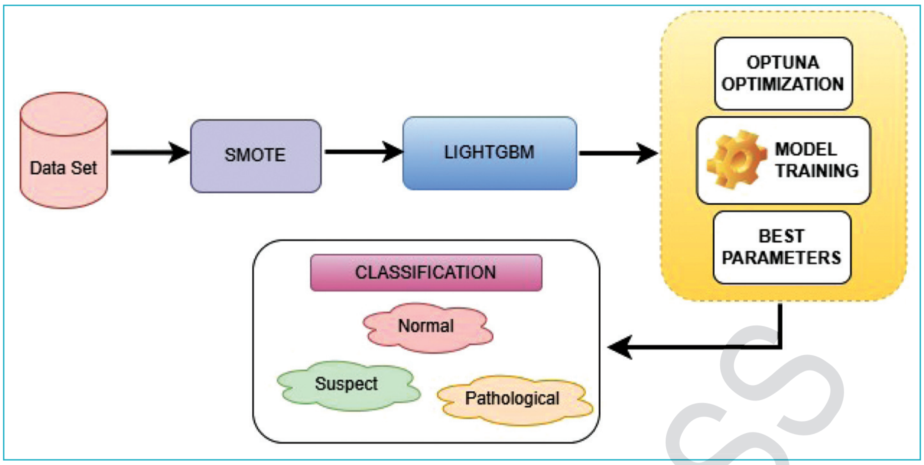

FIGURE 1: Proposed model architecture

timized the model's performance and created a more streamlined and effective model. The architecture of the proposed model is shown in Figure 1.

RESULTS

In this study, the model development process was carried out using the Python programming language and the Colab editor. The dataset was divided into 2 subsets according to the 80% training and 20% test data ratio. The model performances were evaluated using the accuracy, precision, sensitivity, and F1 score metrics. The study used 6 different classifiers [Stochastic Gradient Descent Classifier (SGDC), GB, DT, LR, KNN, and LightGBM]. The dataset and the 6 models mentioned were directly classified in the first step. The resulting complexity matrices are presented in Figure 2.

It can be observed that the SGDC model correctly classified 317 out of 328 healthy class samples, misclassifying 10 as suspicious and 1 as pathological (Figure 2). For the 58 suspicious class samples, it correctly classified 24, while misclassifying 31 as healthy and 3 as pathological. For the 37 pathological class samples, it correctly classified 31, misclassifying 3 as healthy and 3 as suspicious. The GB model correctly classified 320 of 328 healthy class samples, misclassifying 6 as suspicious and 2 as pathological. For the 58 suspicious class samples, it correctly classified 42, misclassifying 14 as healthy and 2 as pathological. For the 37 pathological class

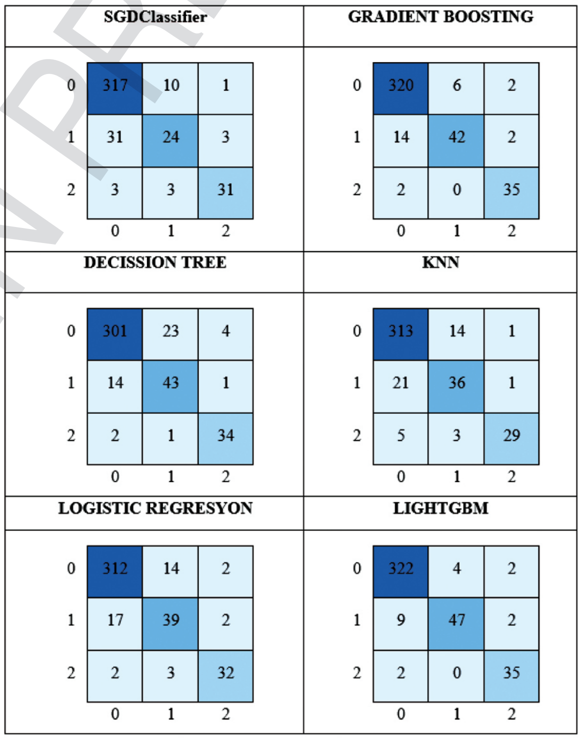

FIGURE 2: Machine Learning Model Complexity Matrices

samples, it correctly classified 35, misclassifying 2 as healthy. The DT model correctly classified 301 of 328 healthy class samples, misclassifying 23 as suspicious and 4 as pathological. For the 58 suspicious class samples, it correctly classified 43, misclassifying 14 as healthy and 1 as pathological. For the 37 pathological class samples, it correctly classified 34, misclassifying 2 as healthy and 1 as suspicious. The

KNN model correctly classified 313 of 328 healthy class samples, misclassifying 14 as suspicious and 1 as pathological. For the 58 suspicious class samples, it correctly classified 36, misclassifying 21 as healthy and 1 as pathological. For the 37 pathological class samples, it correctly classified 29, misclassifying 5 as healthy and 3 as suspicious. The LR model correctly classified 312 of 328 healthy class samples, misclassifying 14 as suspicious and 2 as pathological. For the 58 suspicious class samples, it correctly classified 39, misclassifying 17 as healthy and 2 as pathological. For the 37 pathological class samples, it correctly classified 32, misclassifying 2 as healthy and 3 as suspicious. The LightGBM model correctly classified 322 of 328 healthy class samples, misclassifying 4 as suspicious and 2 as pathological. For the 58 suspicious class samples, it correctly classified 47, misclassifying 9 as healthy and 2 as pathological. For the 37 pathological class samples, it correctly classified 35, misclassifying 2 as healthy.

Based on the results provided above, the performance of each model is generally successful although some errors are observed for each class. In the SGDC model, although the correct classification rate for the healthy class is high, there are misclassifications in the suspicious and pathological classes. The GB model classifies healthy class samples with high accuracy, but misclassifications in the suspicious class are noteworthy. The DT model also achieved high accuracy for the healthy class, but similar errors occurred for the suspicious and pathological classes. The KNN model performs well for healthy class samples, but significant misclassifications are observed in the suspicious class. The LR model makes some misclassifications for each class, but its accuracy is relatively high. Finally, the LightGBM model stands out with its high accuracy in the healthy class and relatively lower error rate in the suspicious class. While all models demonstrate high accuracy for the healthy class, performance improvements are needed for the suspicious and pathological classes. The correct classification of suspicious and pathological classes is critical for the overall success of the model.

Table 1 demonstrates the performance comparisons of the ML models used in this study. Among the evaluated models, LightGBM exhibited the highest performance, achieving 96% accuracy overall and excelling in the suspicious class with 99% accuracy and strong recall and F1 scores. GB also performed well, maintaining a balance between accuracy (94%) and interpretability. In contrast, SGDC showed the weakest performance, particularly in the suspicious class, where recall dropped to 41%, indicating frequent misclassification. Other models, such as KNN and LR, struggled with lower recall rates in critical classes. Overall, LightGBM emerged as the most effective model for fetal health classification.

The LightGBM model, which achieved the highest accuracy among the ML models, was selected in the proposed model. Considering the class performance differences, data balancing was performed using SMOTE, followed by classification with the Optuna optimization method. The resulting confusion matrices are shown in Figure 3.

In the proposed model, out of 331 healthy class samples, 320 were correctly classified, while 10 were misclassified as suspicious and 2 as pathological (Figure 3). Of the 320 suspicious class samples, 315

TABLE 1: Performance Comparisons of the ML Models

	Accuracy (%)			Precision (%)			Recall (%)			F1-Score		
	0	1	2	0	1	2	0	1	2	0	1	2
SGDC	89	88	97	90	64	88	96	41	83	93	50	86
GB	94	94	98	92	87	89	97	72	94	96	79	92
DT	89	90	98	94	64	87	91	74	91	93	68	89
KNN	90	90	97	92	67	93	95	62	78	93	64	85
LG	91	91	97	94	69	88	95	67	86	94	68	87
LightGBM	96	96	99	96	92	89	98	81	94	97	86	92

SGDC: Stochastic Gradient Descent Classifier; GB: Gradient Boosting; DT: Decision tree; KNN: K-Nearest Neighbors; LG: Logistic Regression; LightGBM: Light Gradient Boosting Machine

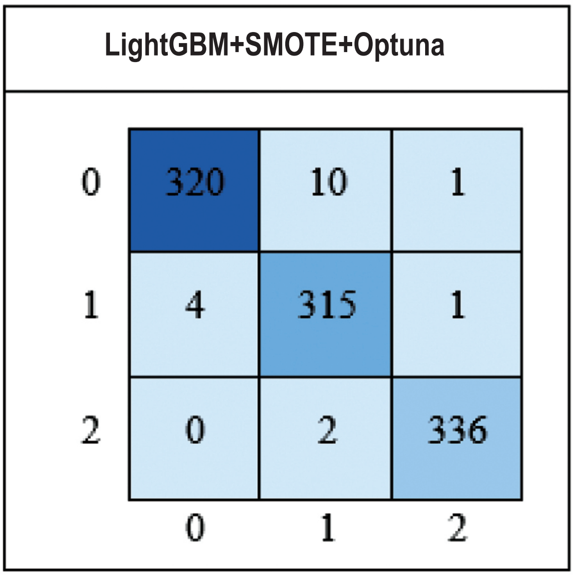

FIGURE 3: LightGBM+SMOTE+Optuna model complexity matrices

were correctly classified, while 4 were misclassified as healthy and 1 as pathological. Of the 338 pathological samples, 336 were correctly classified, while 2 were misclassified as suspicious.

The proposed model achieved the highest accuracy of 98% for the suspicious class, while achieving 99% accuracy for both the healthy and pathological classes (Table 2).

DISCUSSION

Compared to traditional models such as the SGDC, DT, KNN, and Logistic Regression (LG), the proposed model demonstrated superior performance in terms of accuracy, precision, recall, and F1-scores across all 3 classes (healthy, suspicious, and pathological). The SGDC model exhibited weak recall for the suspicious class at 41%, indicating significant difficulty in accurately identifying this category. The DT model achieved a recall of 74% for the suspicious class; however, its precision of 64% suggested frequent misclassifications. While the GB and KNN models performed reasonably well, their recall values for the suspicious class remained suboptimal at 72% and 62%, respectively. By applying SMOTE to balance the dataset, sufficient representation of all classes was ensured during training. Before SMOTE, the suspicious and pathological classes were underrepresented, leading to reduced recall and F1-scores in these categories. The results confirmed that SMOTE effectively mitigated the class imbalance issue. Optuna's systematic hyperparameter tuning further optimized the LightGBM model by identifying the most suitable learning rate, depth, and feature parameters, resulting in the highest classification performance.

The proposed pipeline achieved an overall classification accuracy of 99%, marking a substantial improvement over the models without optimization. As illustrated in the confusion matrix, the proposed model significantly reduced the misclassification rates compared to the baseline models (Figure 3). Notably, the suspicious class, which was previously the most challenging to classify, achieved 98% accuracy and a 97% F1-score, demonstrating the model's enhanced capability in distinguishing this critical category. This study introduces an optimized classification framework for fetal health assessment that integrates LightGBM, SMOTE, and Optuna hyperparameter tuning. The results underscore its superior performance over conventional ML models, particularly in addressing class imbalances and improving the recall for clinically significant classes. These findings highlight the potential of automated ML techniques to advance medical diagnostics and support the development of more precise and reliable fetal health monitoring systems.

Several previous studies have explored fetal health classification using various ML models and achieved promising results. For instance, Özbay et al. applied rule-based classifiers such as Decision Table and PART, reporting an accuracy of 96%.[3] Sharma

TABLE 2: LightGBM+SMOTE+Optuna model performance metric

	Accuracy (%)			Precision (%)			Recall (%)			F1-Score		
	1	2	3	1	2	3	1	2	3	1	2	3
The proposed model	99	98	99	98	96	99	96	98	99	97	97	99

et al. used the Enhanced Binary Bat Algorithm for feature optimization and achieved 96.21% accuracy with a random forest classifier.[4] Yashaswini et al. applied the SMOTE and PCA techniques, reaching an accuracy of 97.58% using a random forest model.[8] Sefidi et al. employed an optimized SVM approach and reported an accuracy of 93.98%.[9] Compared with these studies, our proposed LightGBM model, further enhanced by SMOTE and Optuna-based hyperparameter tuning, achieved 99% classification accuracy. This marks a notable improvement, especially in the accurate classification of minority classes such as the suspicious and pathological categories, which are often more challenging to detect. Our model also demonstrated higher recall and F1-scores for these classes, highlighting its robustness and clinical relevance. These findings suggest that the integration of class balancing and automated hyperparameter optimization can significantly enhance the diagnostic performance of ML models in fetal health assessment.

Additionally, it is important to recognize that while this study focused on automated classification based on CTG signal data, clinical assessments of fetal health are influenced by dynamic physiological factors such as uterine activity and the specific timing of decelerations. For example, in non-stress tests, fetal health classification can vary depending on the phase of the uterine contraction in which a deceleration occurs and the fetus's subsequent response. These nuanced clinical aspects are critical in real-world evaluations but may not be fully captured by ML models that rely solely on static CTG metrics. Therefore, future research should consider integrating contraction phase-specific features and broader clinical parameters to improve the precision and applicability of automated fetal health classification systems.

LIMITATIONS

This study has several limitations that should be noted. First, while the dataset used is widely accepted in fetal health classification research and considered sufficient for ML applications, the study was conducted using data from a single source. Although cross-validation was employed to ensure robustness and reliability, external validation on independent datasets from different populations would further enhance the generalizability of the results. Second, while the LightGBM model provides feature importance scores that contribute to understanding key predictors, we did not integrate advanced explainability techniques such as SHapley Additive exPlanations (SHAP) or Local Interpretable Model Agnostic Explanation (LIME), which could provide deeper insights into the model's decision-making process. Finally, this research focused on classical ML models; incorporating deep learning architectures such as convolutional neural networks (CNNs) or transformer-based models in future studies may offer improved performance and additional comparative insights. Moreover, the current model does not account for the clinical context of uterine contractions, such as the phase-specific occurrence of decelerations, which can significantly influence fetal health assessments in clinical practice.

CONCLUSION

The proposed model demonstrates superior performance compared to traditional models such as the SGDC, DT, KNN, and Logistic Regression (LG). It outperforms these models in accuracy, precision, recall, and F1 scores across all three classes: healthy, suspicious, and pathological. Specifically, the SGDC model exhibited a low recall of 41% for the suspicious class, while the DT model showed a recall of 74%, but with low precision (64%). The GB and KNN models showed reasonable performance, but their recall for the suspicious class remained below optimal. The proposed approach, which used SMOTE for balancing the dataset and Optuna for hyperparameter optimization, led to significant improvements in the classification accuracy, achieving 99% accuracy.

Although LightGBM offers feature importance scores, future studies could integrate explainable artificial intelligence techniques, such as SHAP values or LIME, to enhance the interpretability of decision-making processes. This research primarily focused on traditional ML models. Future work will involve a comparison of LightGBM's performance with deep learning models, such as CNNs, LSTMs, or Transformers, which are capable of capturing intricate temporal dependencies in fetal heart rate signals.

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Conflict of Interest

No conflicts of interest between the authors and / or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Authorship Contributions

***Idea/Concept:** Serpil Aslan, Emre Yalçın; **Design:** Emre Yalçın, Hayriye Tanyıldız; **Control/Supervision:** Serpil Aslan; **Data Collection and/or Processing:** Hayriye Tanyıldız, Emre Yalçın; **Analysis and/or Interpretation:** Emre Yalçın, Hayriye Tanyıldız, Serpil Aslan; **Literature Review:** Emre Yalçın, Hayriye Tanyıldız, Serpil Aslan; **Writing the Article:** Serpil Aslan, Hayriye Tanyıldız; **Critical Review:** Emre Yalçın; **References and Fundings:** Emre Yalçın, Hayriye Tanyıldız; **Materials:** Emre Yalçın, Hayriye Tanyıldız, Serpil Aslan.*

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