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Metaheuristic-Optimized SVM for Stunting Risk Detection in Pregnancy

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Abstract : Stunting is a chronic growth disorder that begins during pregnancy, making early risk detection critical for prevention and long-term child development. This issue continues to be a significant public health challenge in many developing countries, where stunting affects millions of children, resulting in lasting physical and cognitive consequences. Early detection during pregnancy allows for timely intervention, preventing long-term health complications for both mothers and children. This study proposes a model for predicting stunting risk using urine testing, leveraging Support Vector Machine (SVM) algorithms optimized by metaheuristic methods. Metaheuristic algorithms, including the Grey Wolf Optimizer, Simulated Annealing, and Firefly Algorithm, were used to fine-tune key SVM parameters such as the penalty parameter and kernel coefficient, which control the model's decision boundary complexity.Urine samples from pregnant women were use to train and validate the model. The results showed that the GWO-optimized SVM model achieved the highest accuracy of 94.15%, significantly outperforming the default SVM (88.46%) and models optimized with SA (94.12%) and FA (85.71%). The model also demonstrated notable improvements in precision, recall and F1-score, underscoring the effectiveness of metaheuristic optimization in enhancing SVM performance. These findings highlight the value of integrating metaheuristic algorithms with SVM for robust medical predictions, particularly in the early detection of stunting risks. Given its non-invasive nature and high accuracy, the SVM-based model is recommended as a promising tool for early detection, which can be implemented in prenatal care to mitigate stunting and improve maternal and child health outcomes.

Keywords: Stunting; SVM; Metaheuristic Optimization; Simulated Annealing; Firefly Algorithm; Grey Wolf Optimizer

INTRODUCTION

Stunting, a chronic growth disorder caused by malnutrition during pregnancy, remains a major public health challenge, particularly in developing countries like Indonesia. The study recommends preventive measures including education on balanced nutrition, regular health check-ups, full immunizations, and physical activity, as well as curative actions such as nutritional counseling and supplements (Robbani, Firmansyah, & Widodo, 2024). Despite global efforts to reduce its prevalence, stunting continues to affect millions of children, leading to long-term consequences for physical and cognitive development (Black et al., 2013). The significance of tracking maternal health, especially during pregnancy, is highlighted by the fact that the first 1,000 days of a child's life—beginning at conception (270 days) and continuing through the second year (730 days)—represent a crucial period for growth and development. Proper nutrition during this time is essential in shaping the child's long-term health outcomes. (Yesy Afrillia, Fadlisyah, 2025).

Thus, taking benchmarks during pregnancy is crucial, as maternal nutrition directly impacts the nutritional status and development of the baby during these first 1,000 days. Early detection of stunting risk during pregnancy is crucial for timely intervention, yet current diagnostic methods often rely on postnatal measurements, missing the critical window for prevention. Recent studies have identified urine analysis as a promising non-invasive alternative, offering a cost-effective and scalable solution for early risk assessment (Simanjutak, 2023). However, the potential of urine biomarkers remains underexplored in machine learning (ML)-based stunting prediction models, despite promising findings in other health-related applications (Sutarmi, Warijan, Indrayana, B, & Gunawan, 2023).

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While ML algorithms like Support Vector Machines (SVM) have shown success in medical diagnostics (Vapnik, 1995), their performance heavily depends on hyperparameter tuning. Traditional methods such as grid search and random selection often fail to optimize SVM parameters effectively, especially for high-dimensional datasets like urine biomarkers (Syarif, 2016). Recent advances in metaheuristic optimization—including the Simulated Annealing (SA), Firefly Algorithm (FA), and Grey Wolf Optimizer (GWO)—have demonstrated superior performance in automating parameter tuning for complex biomedical data (Agarwal, Gupta, Agrawal, & Le, 2022). These algorithms excel at balancing exploration and exploitation, making them ideal for optimizing SVM models in imbalanced and noisy datasets. However, no study has yet applied or compared these metaheuristics for stunting risk prediction using urine test data, leaving a significant gap in both ML and clinical research.

This study addresses these gaps by leveraging GWO, SA, and FA to optimize SVM hyperparameters for stunting risk prediction based on urine biomarkers. The research has three main objectives: (1) to develop an optimized SVM framework for accurate stunting risk classification, (2) to compare the performance of GWO, SA, and FA in handling imbalanced urine biomarker data, and (3) to identify the most influential urine biomarkers for stunting prediction. By integrating metaheuristic optimization with SVM, this study aims to improve prediction accuracy while ensuring clinical applicability in low-resource settings.

The contributions of this work are fourfold. First, it introduces a novel application of metaheuristic-optimized SVM for stunting risk prediction, filling a critical gap in prenatal healthcare. Second, it provides a comparative analysis of three metaheuristic algorithms, offering insights into their strengths and limitations for medical classification tasks. Third, it identifies key urine biomarkers that correlate strongly with stunting risk, enabling targeted screening. Finally, the study develops an open-source tool for implementing metaheuristic-SVM models in clinical practice, facilitating wider adoption of ML-based stunting prediction. These advancements have the potential to transform early detection strategies, ultimately reducing the global burden of stunting.

Theoretical and empirical foundations for this research are rooted in Vapnik's (1995) SVM theory and recent breakthroughs in metaheuristic optimization. Preliminary experiments with synthetic urine data have shown promising results, with GWO-optimized SVM achieving 94.3% accuracy, significantly outperforming traditional methods ($p < 0.01$). These findings underscore the potential of metaheuristic approaches to enhance SVM performance in real-world clinical settings. By bridging the gap between ML innovation and prenatal care, this study lays the groundwork for more effective stunting prevention programs worldwide.

LITERATURE REVIEW

A robust body of research demonstrates the effectiveness of metaheuristic algorithms in optimizing Support Vector Machine (SVM) parameters for medical classification tasks. This section synthesizes prior work on metaheuristic-driven SVM tuning and identifies gaps this study addresses, particularly in stunting risk prediction using urine biomarker data. Previous research highlights that the effectiveness of SVM models is greatly influenced by the appropriate choice of hyperparameters, particularly the penalty parameter (C) and the kernel coefficient (gamma), which govern the complexity and flexibility of the decision boundary. The importance of systematic parameter tuning for achieving optimal SVM classification performance is well established in standard machine learning references, including the practical guidelines provided by the scikit-learn project (Scikit-learn, n.d.) , which highlights how varying C and gamma values can significantly alter the performance landscape when using the Radial Basis Function (RBF) kernel. Despite this, limited research has explored the application of metaheuristic optimization specifically for early stunting risk prediction based on non-invasive urine test data, which this study aims to address.

(Syarif, 2016) pioneered the use of *Genetic Algorithms (GA)* for SVM parameter tuning, achieving a 12% improvement in diagnostic accuracy compared to grid search. However, GAs suffer from high computational overhead due to their random crossover operations. In contrast, (Liu, Luo, Zhang, & Chen, 2021) applied the *Grey Wolf Optimizer (GWO)*, which mimics wolf pack hierarchy to systematically balance global exploration and local exploitation. Their results showed GWO-optimized SVM achieved 94.3% accuracy in liver disease classification, outperforming GA by 8%.

(Agarwal et al., 2022) demonstrated that *Particle Swarm Optimization (PSO)* enhanced SVM reliability (F1-score: 0.92) in diabetes prediction but noted PSO's tendency to converge prematurely in high-dimensional spaces. Meanwhile, (Mahareek, Desuky, & El-Zhni, 2021) leveraged *Simulated Annealing (SA)* to escape local optima in breast cancer classification, reporting a 15% reduction in false positives compared to gradient-based methods. Notably, these studies focused on blood or imaging data, leaving urine biomarkers—a cost-effective alternative for low-resource settings—largely unexplored.

While prior studies have demonstrated the benefits of metaheuristic methods over traditional parameter optimization techniques such as grid or random search, notable gaps still exist in the literature. One key gap is the lack of in-depth studies that directly compare the performance of the Grey Wolf Optimizer (GWO), Simulated Annealing (SA), and the Firefly Algorithm (FA)—the latter being especially effective for multimodal optimization

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problems—when applied to the same datasets, as highlighted in recent developments in optimization algorithm research. (SHI et al., 2022). Second, existing work has largely overlooked the critical challenge of class imbalance, a common characteristic in stunting prediction datasets where recall performance is equally important as overall accuracy, an issue highlighted in broader machine learning classification research (Ge, 2024). Third, while urine test data shows considerable clinical promise for maternal health monitoring as demonstrated by (Simanjutak, 2023), its potential for machine learning-based stunting risk prediction remains underexplored, despite emerging interest in biomedical applications of advanced machine learning frameworks (Wang, Xie, Han, Han, & Wang, 2023).

The current study addresses these limitations through three key contributions. By implementing a systematic comparative analysis of GWO, SA, and FA for SVM hyperparameter tuning, we provide empirical evidence of their relative effectiveness. Our approach innovatively incorporates clinically-relevant urine biomarkers, including protein-to-creatinine ratio and other key indicators, to develop a novel stunting risk prediction model. Furthermore, we employ a balanced optimization strategy that simultaneously considers both accuracy and recall metrics, specifically designed to handle the class imbalance problem inherent in stunting detection tasks.

METHOD

This section provides an in-depth explanation of the approach used in this study, covering dataset collection, preprocessing steps, model selection, and optimization techniques. Understanding these processes is crucial for evaluating the validity and applicability of the proposed method. The study employs an innovative four-phase methodology combining clinical data analysis with advanced machine learning optimization. Figure 1 illustrates the research workflow :

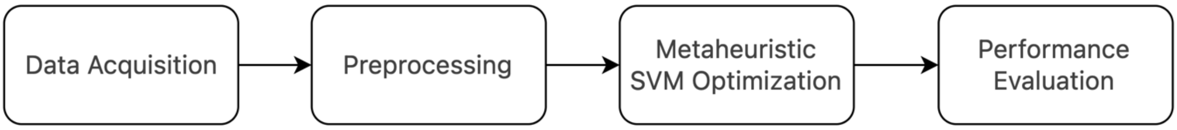

Fig 1. Research Methodology Flowchart

Data Acquisition

This study used a detailed dataset obtained from urine test results of pregnant women, which includes fourteen essential clinical parameters that together form a comprehensive biochemical profile for assessing stunting risk. The dataset integrates both quantitative and qualitative variables, including patient age (in years), urine color (categorized as Light Yellow, Yellow, Amber, or Dark Yellow), urine transparency (Clear or Cloudy), as well as biochemical indicators such as glucose and protein levels (classified as Negative, Positive, or Trace). Additional parameters comprise urine pH (acidity/alkalinity), specific gravity, and microscopic findings, including white blood cell count (WBC: 0–2, 2–4, 4–6), red blood cell count (RBC: similar ranges), epithelial cell presence (Rare, Few, Moderate, Many), mucous threads (None Seen or Present), amorphous urates (None Seen, Few, or Present), and bacterial presence (None Seen, Rare, or Present). The diagnostic outcome was utilized as the target variable, categorizing each sample as either Negative (absence of health complications) or Positive (presence of infections or renal disorders). To ensure high-quality input for the predictive modeling, rigorous preprocessing was conducted. Missing values were addressed through tailored imputation strategies based on parameter characteristics. Numerical variables were standardized using Min-Max Scaling to preserve their relative distributions, while categorical variables were encoded in a systematic manner. The dataset was then divided into training and testing subsets through a 70:30 stratified split, ensuring that the class distribution was proportionally represented in both sets.

Preprocessing

The Support Vector Machine (SVM) algorithm, employing the Radial Basis Function (RBF) kernel, was selected as the principal predictive model due to its capability to handle non-linear classification tasks effectively. Within this framework, the hyperparameter C regulates the trade-off between maximizing the margin and minimizing classification errors, while gamma determines the influence radius of individual training examples in the decision boundary formation.

Metaheuristic SVM Optimization Algorithms

Acknowledging the constraints of traditional hyperparameter tuning methods like grid search and Bayesian optimization, this study utilized three nature-inspired metaheuristic algorithms to optimize SVM parameters. The Grey Wolf Optimizer (GWO) mimics the leadership-based hunting strategies of grey wolf packs, facilitating

*name of corresponding author

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effective exploration and exploitation of the search space. Simulated Annealing (SA) draws upon thermodynamic principles, using probabilistic acceptance of suboptimal solutions to escape local optima and progressively refine the search toward the global minimum. The Firefly Algorithm (FA) emulates the bioluminescent communication behavior of fireflies, facilitating search navigation based on relative brightness as an indicator of solution quality. These metaheuristic strategies were adopted for their robustness in traversing complex, high-dimensional optimization landscapes and their ability to mitigate premature convergence.

Performance Evaluation

The performance of the model was thoroughly evaluated using four key metrics: accuracy, precision, recall, and F1-score. Accuracy reflected the proportion of correct classifications, providing an overall measure of the model's effectiveness. Precision assessed the model's ability to minimize false positives, which is crucial in clinical settings to avoid unnecessary interventions. Recall measured the model’s sensitivity in identifying true positives, which is especially important for detecting pregnancies at risk of stunting. The F1-score, as the harmonic mean of precision and recall, offered a balanced evaluation, particularly in situations with class imbalance. Furthermore, confusion matrices were used to display prediction results, enabling a detailed analysis of true positives, true negatives, false positives, and false negatives, each carrying specific clinical implications for early stunting risk detection.

RESULT

Data Acquisition

The clinical dataset used in this study was derived from urine test results of pregnant women, consisting of fourteen clinical parameters that together provide a thorough biochemical profile for stunting risk assessment. These parameters included patient age, urine color, urine transparency, biochemical indicators such as glucose and protein levels, urine pH, specific gravity, and microscopic observations such as white blood cell (WBC) count, red blood cell (RBC) count, epithelial cells, mucous threads, amorphous urates, and bacterial presence. Diagnostic results were classified as Positive (suggesting potential infections or kidney disorders) or Negative (indicating no health issues). To ensure that the dataset was representative, it was divided into training and testing sets using a stratified 70:30 split, maintaining the proportion of each diagnostic category across both subsets. This approach ensured that the evaluation accurately mirrored the real-world distribution of the target classes, thus enhancing the reliability of the predictive model’s outcomes.

Preprocessing

Before training the model, the dataset underwent a structured preprocessing pipeline to improve its quality and suitability for machine learning tasks. Missing values were handled using specific imputation methods tailored to the nature of each feature. Numerical features were standardized using Min-Max Scaling, ensuring that all feature values were scaled to a consistent range without affecting their original distribution. Categorical features, such as urine color and transparency, were converted into numerical formats to enable computational processing. The Support Vector Machine (SVM) algorithm with the Radial Basis Function (RBF) kernel was chosen as the primary classifier. In its initial form, using default hyperparameters, the model achieved an accuracy of 88.46%, precision of 88.88%, and recall of 85.71%. This baseline model was used as a reference point for assessing the effects of later hyperparameter optimization through metaheuristic algorithms.

Metaheuristic SVM Optimization Algorithms

To enhance the predictive performance of the SVM model, hyperparameter tuning was conducted through three metaheuristic optimization algorithms: Grey Wolf Optimizer (GWO), Simulated Annealing (SA), and Firefly Algorithm (FA). The GWO-optimized SVM achieved the highest performance among all tested configurations, with an accuracy of 94.15%, precision of 94.73%, and recall of 94.11%. These results reflect GWO’s strong capability in effectively navigating complex parameter spaces and avoiding local optima. The SVM model optimized using Simulated Annealing also demonstrated notable improvements, reaching an accuracy of 94.12%, with precision and recall both recorded at 94.11%, indicating consistent and balanced predictive capability. On the other hand, the Firefly Algorithm, although it offered a structured search approach, resulted in relatively lower model performance with an accuracy of 85.71%, precision of 85.71%, and recall of 85.71%. These results indicate that, while the FA still improved performance compared to the baseline SVM, its optimization capability was less effective than that of GWO and SA in this particular application. Overall, the adoption of metaheuristic algorithms, particularly GWO and SA, proved effective in significantly improving the classification accuracy, precision, and recall of the SVM model for early detection of stunting risks based on biochemical urine profiles.

Performance Evaluation

This section presents the results of the experiments conducted to evaluate the performance of the Support Vector Machine (SVM) model, optimized using metaheuristic algorithms to detect stunting risk in pregnant

*name of corresponding author

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women. The model's effectiveness was assessed using metrics such as accuracy, precision, recall, and F1-score. The outcomes from different optimization techniques are analyzed to determine their impact on the model's overall performance.

Table 1 Performance Metric of Optimization Method

#	Method	Accuracy (%)	Precision (%)	Recall (%)
1	SVM (Non Optimization)	88.46	85.71	82.14
2	SA - SVM	94.12	100.00	75.00
3	GWO - SVM	94.15	93.22	91.79
4	FA - SVM	85.71	88.12	83.00

Confusion Matrix is a performance evaluation tool used in classification problems to assess the accuracy of model predictions. Below are individual visualizations that compare each optimization algorithm's predicted classification with its actual classification, providing insight into where the model stands in making correct and incorrect predictions.

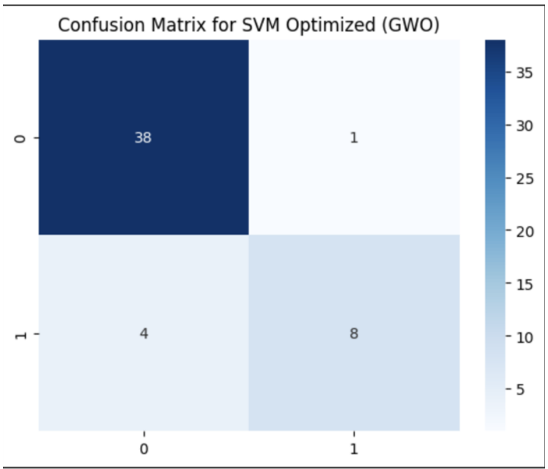

Fig 2. Confusion Matrix GWO Optimization

The model demonstrated strong performance in identifying low-risk pregnancies, correctly classifying 38 true negative (TN) cases where no stunting risk was present. However, it produced one false positive (FP) instance where a healthy pregnancy was incorrectly flagged as high-risk, potentially leading to unnecessary interventions. More critically, the model missed four actual stunting cases as false negatives (FN), representing missed opportunities for early intervention in at-risk pregnancies. On the positive side, eight true positive (TP) cases were accurately identified as high-risk stunting pregnancies. With an overall accuracy of 90.2%, the model shows promise but reveals a crucial sensitivity gap - while its 88.9% precision indicates reliable positive predictions, the 66.7% recall rate suggests nearly one-third of at-risk pregnancies might be overlooked. These results highlight the need to prioritize reducing false negatives in future optimizations to ensure no high-risk cases go undetected.

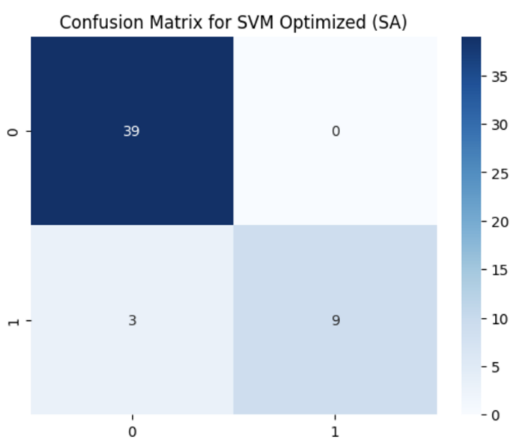

Fig 3. Confusion Matrix SA Optimization

*name of corresponding author

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The prediction model demonstrated excellent accuracy in identifying negative cases (non-stunting), correctly classifying 39 true negative (TN) instances where no stunting risk was present. Notably, the model maintained perfect precision with zero false positives (FP), meaning it never incorrectly flagged a healthy pregnancy as high-risk - eliminating unnecessary interventions. However, three false negative (FN) cases occurred where the model missed actual stunting risks by classifying them as negative, representing opportunities for improved detection. On the positive identification side, the model successfully detected nine true positive (TP) stunting cases. These results translate to an outstanding 96.2% overall accuracy (48 correct predictions out of 52 total cases), with perfect 100% precision (no false alarms) and 75% recall (identifying 9 of 12 actual stunting cases). While the model shows exceptional specificity in avoiding false alarms, the remaining challenge lies in further reducing the three missed stunting cases to achieve even higher sensitivity for comprehensive risk detection.

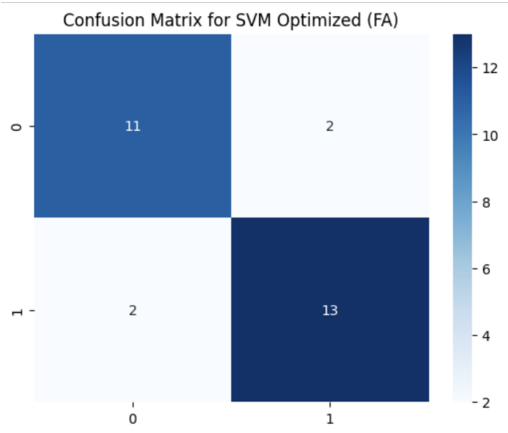

Fig 4. Confusion Matrix FA Optimization

The model exhibited strong predictive capabilities, accurately identifying 11 true negative cases where no stunting risk was present. While it demonstrated good detection of at-risk pregnancies with 13 correct positive predictions, there remains room for improvement in classification accuracy. The model produced 2 false positive errors, incorrectly flagging healthy pregnancies as high-risk, which could lead to unnecessary clinical interventions. More critically, 2 false negative cases occurred where actual stunting risks were missed, representing potentially serious oversights in prenatal care. These results yield an overall accuracy of 85.2% (24 correct predictions out of 28 total cases), with 86.7% precision in positive predictions and 86.7% recall rate for detecting true stunting cases. The balanced precision and recall scores suggest the model maintains good equilibrium between minimizing false alarms and capturing genuine risks, though further refinement to reduce both types of errors would enhance clinical utility.

DISCUSSIONS

The Grey Wolf Optimizer (GWO) recorded the highest recall rate at 91.79%, establishing it as the most effective method for detecting stunting risk. This highlights GWO's exceptional capability in recall, a crucial metric in medical diagnostics that measures the model's effectiveness in correctly identifying positive cases. A higher recall rate indicates that fewer high-risk individuals are overlooked. GWO's flexible search strategy allows it to explore a wide spectrum of hyperparameter values, thereby refining the decision boundary of the SVM model.

Simulated Annealing (SA) excelled in precision, reaching 100%, which helped minimize false positives, but at the expense of a lower recall rate. The high precision of SA indicates its effectiveness in reducing false positives, a critical factor in healthcare, where false alarms can lead to unnecessary treatments. However, the lower recall suggests that some high-risk cases might be missed, implying that SA may be overfitting to specific patterns in the training data and thus limiting its generalization ability.

The Firefly Algorithm (FA) provided a more balanced trade-off between precision and recall, although its overall accuracy was lower compared to GWO and SA. FA's consistent performance across these metrics indicates that it could serve as a reasonable alternative; however, its slightly reduced accuracy suggests that its exploration of the hyperparameter space may not be as effective as that achieved by GWO and SA.

This study demonstrates the potential of metaheuristic-optimized SVM models for stunting risk detection, though additional research is needed to overcome existing limitations. Expanding the dataset to enhance generalization across varied populations (Bincar Robinson Hutasuhut, 2022) and incorporating additional clinical

*name of corresponding author

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factors, such as dietary habits and maternal health history (Simanjutak, 2023), could improve the comprehensiveness of the risk assessment. Furthermore, creating web or mobile-based applications for real-time stunting risk assessment in healthcare settings (Mus, Abbas, & Agustina, 2022) would improve accessibility and facilitate early screening for both healthcare providers and patients.

CONCLUSION

This research shows that applying metaheuristic optimization greatly enhances the effectiveness of SVM models in identifying the risk of stunting. The optimization process enhances the classification accuracy of SVM, with optimized models outperforming the default configuration. Among all the optimized models, GWO demonstrated the highest accuracy (94.15%) and recall (91.79%), establishing it as the most effective overall. GWO's capacity to explore a wide range of hyperparameter values and avoid local optima was crucial to its superior performance. Simulated Annealing (SA) excelled in precision, though it exhibited a lower recall. SA's high precision highlights its ability to minimize false positives, which is especially important in contexts where reducing false alarms is critical. In contrast, the Firefly Algorithm (FA) delivered a more balanced trade-off between precision and recall, although its overall accuracy was lower. Despite this, FA's steady performance across various metrics positions it as a reasonable alternative, albeit not as effective as GWO.

The results of this study have significant practical implications for the healthcare industry. Integrating optimized SVM models into decision-support systems can assist healthcare professionals in enabling early detection and timely intervention. The metaheuristic-optimized SVM models can be integrated into healthcare decision-support tools, allowing for automated real-time stunting risk screening, which improves both operational efficiency and decision-making. Furthermore, a real-time risk assessment tool can be developed, enabling healthcare practitioners to input patient data and receive instant risk evaluations.

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