Environment Aspects and Daily Life-Threatening Risk Prediction for Improving Public Health Using Ensemble Learning Techniques

Omprakash Dewangan[1], Vasani Vaibhav Prakash[2]
[1]*Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India*
[2]*Research Scholar, Department of CS & IT, Kalinga University, Raipur, India*

KEYWORDS

Work-Life Balance, Public Health, Stress Management, Feature Selection, Ensemble Learning, MSSVM, DSXG-Boost

ABSTRACT

Increasing work nature in the fastest world need relaxing to maintain public health is important. But the continuous imbalance of work nature in human daily life doesn't have time to consecrate the health with leads life threatening facts such as work tension, management stress, job professional, family needs, improper periodic work cycle, and soon. By analyzing the daily public life threatening risk prediction based on Feature selection and classification to category the public health to recommend for phycological treatment. By suggesting treatment schedule are important to balance the public health Lifecyle to make stress free life to spent with nature. Most of prevailing techniques analyse the life-threatening issues, but the features are improperly to taken without the mutual relation cause poor accuracy in precision and classifications rate with more false prediction rate. To tackle this issue, to propose an optimized ensemble learning Techniques based on multi scalar support vector machine (MSSVM) with deep scaled XGboost classifier (DSXG-boost) to improve the prediction accuracy. Initially the public life Cycle dataset is collected and to make normalization using Min-max normalization. Then the Public Life Threat Impact Rate (PLTIR) is analysed to marginalize the heath affecting features. Then then stress margin dependencies feature limits are selected with support of MSSVM. The selected features are grouped in cluster margins and classified with deep scaled XG boost algorithm to predict the active and inactive heath margin be categorized by risk threaten class. The proposed system prove the prediction accuracy in higher precision are by selecting mutual dependencies of health affection feature limits and best recall rate to improve the performance. Based on the predicted class, the categorized life threaten risk peoples are recommends to make phycological treatment to protect the public life cycle.

1. Introduction

In today's fast-paced world, the nature of work has become increasingly demanding, often leaving individuals with little time for rest and relaxation [1]. Environment aspects and daily life-threatening risk prediction for improving public health using ensemble learning Techniques The field of environmental health has increasingly recognized the importance of understanding how various environmental factors can impact human health and well-being nature [2]. Predicting and mitigating risks that threaten public health has emerged as a key priority, as exposure the human work nature have various risks such as work pressure, improper time management, improper health maintenance, stress and so on [4]. Ensemble learning techniques, which combine multiple models to improve predictive performance, have shown promise in this domain [3] This continuous imbalance in daily life has led to a concerning rise in life-threatening issues, such as work-related stress, management challenges, professional pressures, family responsibilities, and irregular work cycles [21]. These factors have a significant impact on public health, necessitating a comprehensive approach to address the problem. The traditional methods of analysing life-threatening issues often fall short due to the improper selection of features and the lack of consideration for the mutual relationships between them [5]. This leads to poor accuracy in prediction and classification, with a higher rate of false positives. This research propose an innovative ensemble learning approach that combines the strengths of MSSVM and DSXG-boost to enhance the accuracy and reliability of predicting and categorizing public health risks associated with work-life imbalance [7]. The proposed method aims to address the limitations of the existing techniques by focusing on the selection and analysis of the most relevant features that contribute to the life-threatening risks, while also considering the mutual dependencies and interactions between these factors.

Methodology:The proposed framework consists of the following key steps: Data Collection and Normalization:The public life cycle dataset is collected and normalized using Min-max normalization to ensure consistent data representation. Public Life Threat Impact Rate (PLTIR) Analysis: The PLTIR is analysed to identify and marginalize the health-affecting features that contribute to the life-threatening risks. Feature Selection using MSSVM: The MSSVM algorithm is employed to select the most relevant features based on their mutual dependencies and importance in predicting the health risks. Feature Clustering and Classification with DSXG-boost: The selected features are grouped into clusters based on their similarities, and the DSXG-boost classifier is used to accurately predict the active and inactive health risk categories. Risk Categorization and Treatment Recommendations: Based on the predicted health risk classes, individuals are categorized and recommended for appropriate psychological treatment to maintain a balanced and stress-free life. The proposed ensemble approach leverages the strengths of MSSVM and DSXG-boost to achieve higher prediction accuracy and better recall rates compared to the existing techniques. The MSSVM algorithm ensures the selection of the most relevant features by considering their mutual dependencies, while the DSXG-boost classifier provides accurate classification of the health risk categories.

Related work

The survey covers the concentrations in public health sector , challenges in existing methods in which is for accurately predicting health risks and threats to improve the overall well-being of the community. In this regard, the integration of advanced machine learning techniques can contribute significantly to enhancing the predictive accuracy of public health models. The Machine Learning (ML) models predict the well-being of physicians, evaluate health influencers, and analyze insights into work-life balance [6]. However, work satisfaction can be impacted by variables such as weekly hours worked and experiences of harassment. Moreover, they offer up-to-date evidence that forecasts the extent of the connection between work schedules and different social and family factors [22]. An optimal support vector machine (SVM) model was implemented by implementing a comparison model between prediction functions and multiple regression models to assess the highest accuracy of work-life balance predictions [8]. Several studies have shown the application of Artificial Neural Network (ANN) models in structuring and interpreting datasets for analyzing multiple workers [9]. They enhance public health and compare the work-life balance and quality of life between employees in Lithuania public and private sectors [26]. The understanding of work-life balance is then developed through global, national, and temporal dimensions [11]. Moreover, it assesses the gaps and limitations in current analyses of the future of work-life balance in an increasingly connected [10]. They assume a socioecological framework to characterize employee work-life balance determinants. These suggest new approaches to improving employee well-being and promoting long-term organizational growth [12]. The Naive Bayes (NB) algorithm can predict the critical role of work-life balance in its relationship with various factors [13]. Organizations increasingly utilize the best-performing Extreme Gradient Boosting (XGB) ensemble technique based on ML methods to predict employee turnover [14]. However, it presents a range of organizational challenges because of its detrimental effects on growth objectives and workplace productivity [23]. A predictive model for customer sentiment in the B2B e-commerce sector was created by assessing the SVM model's forecasting capabilities [18]. Moreover, a data-centric methodology for crafting predictive and retention strategies was discovered, diverging from the traditional management heuristics in the B2B e-commerce field [24]. Based on multivariate clinical data, the author [16] suggested a Light Gradient Boosting Machine (LGPM) method to forecast life-threatening occurrences in intensive care units [15]. A method using the Gaussian Mixture Model (GMM) is suggested for pooled hypertension risk prediction through multiple agents, aiming to identify and estimate missing values in time series data while offering personalized hypertension risk forecasts [17]. Conducting a risk assessment can help identify critical factors contributing to an employee's decision to improve their overall health [25]. They assessed the importance of each feature with the Recursive Feature Elimination (RFE) algorithm and utilized cross-validation to pinpoint the top feature subset. Yet, no dependable techniques exist for predicting the progression of hypertension [19]. Identify common behavioral patterns using an Intelligent Fuzzy-Based Approach (IFA) to analyze effective outcomes in hypertension prevention [20]. Furthermore, the proposed model is optimized for real-time evaluation using a hypertension dataset from primary healthcare facilities.

2. Methodology

To tackle this issue, we propose an optimized ensemble learning technique based on a Multi-Scalar

Support Vector Machine (MSSVM) and a Deep-Scaled XGBoost Classifier (DSXG-Boost). This approach aims to improve the prediction accuracy and provide a more reliable solution for addressing the public health crisis. The first step in the proposed system is to collect the public life cycle dataset and normalize it using Min-Max normalization. This ensures that the data is on a consistent scale, making it more suitable for analysis. Next, the Public Life Threat Impact Rate (PLTIR) is analyzed to identify the features that have the most significant impact on public health

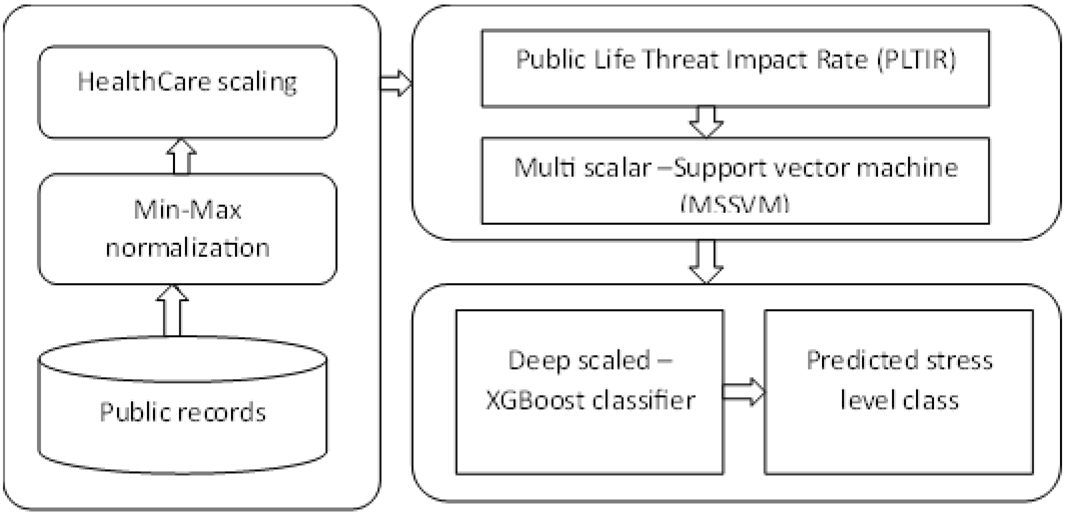

Figure 1. proposed workflow diagram MSSVM-DS-XGBoost

The stress margin dependencies and feature limits are then selected using the MSSVM, which takes into account the mutual relationships between the health-affecting factors. Figure 1 shows the proposed workflow diagram MSSVM-DS-XGBoost .The selected features are then grouped into cluster margins and classified using the Deep-Scaled XGBoost algorithm. This algorithm is designed to provide a more accurate prediction of the active and inactive health margins, categorizing them by risk-threatening class. The proposed system aims to achieve a higher level of prediction accuracy by selecting the mutual dependencies of health-affecting feature limits and ensuring a better recall rate to improve overall performance. Based on the predicted classes, the categorized life-threatening risk individuals are recommended for psychological treatment to protect their overall well-being and maintain a healthy work-life balance.

Data Collection and Preprocessing: The first step in the proposed system is to collect the Public Life Cycle dataset, a comprehensive repository of data related to various aspects of public health. To ensure the reliability and consistency of the data, a preprocessing step involving min-max normalization is performed. This normalization technique helps to scale the data within a specific range, reducing the impact of outliers and improving the overall data quality.

Public Life Threat Impact Rate (PLTIR) Analysis: The next step in the proposed system is the analysis of the Public Life Threat Impact Rate (PLTIR). This metric is used to identify the features that have the most significant impact on public health threats. By marginalizing the health-affecting features, the system can focus on the most crucial factors that contribute to health risks, enabling more targeted and effective interventions. The separation points were chosen using a purity index. Following that, a summary of how each attribute matched across all decision trees in the model is presented. The following method is used to determine the purity index: The development of the entire system has as its main goal maximizing the purity of each segment. According to equation, stress purity is the level of resemblance between the threat features affected in public health.

$$\text{Stress impact purity Gini index} = 1 - p_j^3$$

Here, p_j^3 is the probability of feature by getting stress which the feature limits get affected by threading factors marginalized with impact threshold rate. And also the correlation coefficient

r_{jk}between two feature values $x_j and x_k$ is mathematically given by

$$r_{jk} = \frac{S_{jk}}{S_j S_k} = \frac{\sum_{i=1}^{n}(x_{ij}-\overline{x_j})}{\sqrt{\sum_{i=1}^{n}(x_{ij}-\overline{x_j})^2}} \frac{(x_{ik}-\overline{x_k})}{\sqrt{\sum_{i=1}^{n}(x_{ik}-\overline{x_k})^2}}$$

Where S_{jk} is the covariance between jth and kth variable. The correlation heat map generated for the 8 selected variables corresponds to the equation

$$Correlation\ Matrix\ (C_m) = \begin{vmatrix} 1 & r_{12} & r_{13} \\ r_{21} & 1 & r_{23} \\ r_{31} & r_{32} & 1 \\ r_{41} & r_{42} & r_{43} \\ r_{51} & r_{52} & r_{53} \\ r_{61} & r_{62} & r_{63} \end{vmatrix}$$

If the correlation between two features exceeds 0.9, one of the two features can be eliminated otherwise the features are retained (Cm) with the feature limits are closer to each other to average into mean rate. By creating correlation matrix to get the ideal points of feature dependencies on representing stress facts

Feature Selection using MSSVM: The selected features from the PLTIR analysis are then subjected to a feature selection process using the multi-scalar support vector machine (MSSVM) technique. MSSVM is a powerful tool that can capture the complex dependencies and relationships between different feature dimensions, ensuring the selection of the most relevant and informative features for the prediction task. The ensemble meta-algorithm that makes weak learners strong and significantly shrinks the amount of data that machine learning algorithms need to work with. The momentum method aims to make the prediction more accurate.

Step1: let p is positive and g is negative and then taken sample $(C_m(S_i, y_i)$ and $W_j = \frac{1}{2}$ is a sample input dataset and T is the final iteration

Step2 : the normalized $w_{i,j} \leftarrow w_{i,j}$ is probability of distribution and N is the number of features

$\xi_t = \sum_r w_{i,j} |h_1(x_1) - y_{1|}2$

Step3: least classification error is $W_1 = \frac{1}{2} \ln\left[\frac{1}{\xi_t^l} - 1\right]$

Step4: normalized weight calculated equation

$$w_{t+1,j} = w_{i,j} e^{-w_1^1 h(S^1)}$$

Step 5: Finalized fearer selection hypothesis

$$H(S) = sgn \sum_{t-1}^{T} w_1\, e^{-w_1^1 h(S^1)}$$

The following equations illustrate how the maximum distance between the hyperplane and the boundary becomes an optimization problem:

$w^T x + k = 0$

$min = \frac{1}{2}(w^T w)$

$y_i(w^T x_i + k) > 1$

Here $w^T x + k$ is regularization parameter the respective positive and negative support vectors

Step 6 The margin is then denoted by the following equation:

$$\frac{w}{||w||}(x_+) - (x_+) = \frac{w^t\big((x_+)-(x_+)\big)}{||w||} = \frac{2}{||w||}$$

Step 7 The classifier is expressed as the sum over the support vectors in the following equation

$$f(x) = sgn\langle\sum_{i=1}^{N} y_i \alpha_i Q(+x) + b)$$

Here x_i is the support vector machine data, N is the number ship class, $Q(x_i, x)$ is the linear kernel equation The algorithm returns the maximum supported features based on the risk class which is mutually supported to the public heath related life threading factors. The features are supported to reduce the dimension class by actively insufficient risk weights are balanced depends on the risk by categorization.

Feature Clustering and Classification with DSXG-Boost: The selected features from the MSSVM process are then grouped into cluster margins based on their dependencies and relationships. These clustered features are then classified using the deep-scaled XGBoost (DSXG-Boost) algorithm. DSXG-Boost is a modified version of the popular XGBoost algorithm, which incorporates a deep learning-based scaling mechanism to enhance the model's ability to capture complex patterns and relationships within the data. This approach allows for more accurate categorization of the active and inactive health margins, enabling the identification of high-risk individuals or groups.

Algorithm DSXG-ADABOOST

Initialize the observation weights, $f(x)W_i = \frac{1}{C_m}$, $i = 1,2,3 \ldots M$

For $n = 1 to\ N$:

- Fit a classifier $G_n(f(x))$ to the training data using weights W_i

  By introducing gradient boosting the over fitting feature dependencies are avoided to increase the capabilities of each X values have redundant errors which is calculated as,

$$G_n(x) = Wi * \frac{\partial L\left(y, f^{(m-1)}(x) + f_m(x)\right)}{\partial f_m(x)} = 0$$

The Loss function is calculated by

$$(f_m) \approx \sum_{i=1}^{n}[g_m(x_i)f_m(x_i) + \frac{1}{2}h_m(x_i)f_m(x_i)^2] + const$$

- $\propto \sum_{j=1}^{T_m}\sum_{i\in R_{jm}}[g_m(x_i)w_{jm} + \frac{1}{2}h_m(x_i)w_{jm}^2]$

The Loss function is calculated by

$$(f_m) \approx \sum_{i=1}^{n}[g_m(x_i)f_m(x_i) + \frac{1}{2}h_m(x_i)f_m(x_i)^2] + const$$

[10]

- $\propto \sum_{j=1}^{T_m}\sum_{i\in R_{jm}}[g_m(x_i)w_{jm} + \frac{1}{2}h_m(x_i)w_{jm}^2]$
- Compute the error err_n
- Compute $\alpha_m = log\frac{(1-err_n)}{err_n}$

$$L(f_m) \propto \sum_{j=1}^{T_m} G_{jm}w_{jm} + \frac{1}{2}H_{jm}w_{jm}^2$$

$Where\ G_{jm}(x_i) is\ the\ sum\ of\ gradient\ and\ H_{jm}(x_i) is\ the\ sum\ of\ hessian$

$$w_{jm} = -\frac{G_{jm}}{H_{jm}}, j = 1,2, \ldots T_m$$

Including regularization parameter the loss function is given by

$$L(f_m) \propto \sum_{j=1}^{T_m}\left[G_{jm}w_{jm} + \frac{1}{2}H_{jm}w_{jm}^2\right] + \gamma T_m + \frac{1}{2}\lambda\sum_{j=1}^{T_m} w_{jm}^2 + \alpha\sum_{j=1}^{T_m}\left|w_{jm}\right|$$

$$= \sum_{j=1}^{T_m}[G_{jm}w_{jm} + \frac{1}{2}\left(H_{jm}+\lambda\right)w_{jm}^2 + \alpha\left|w_{jm}\right|] + \gamma T_m$$

$$where\ \gamma\ is\ the\ penalization\ term, \lambda\ \&\ \alpha\ are\ the\ regularization\ parameter\ L_1, L_2$$

This ultimately improves the accuracy of the predictive models. Another advantage of this approach is its enhanced speed by adopting parallel processing. Thus XGBoost is preferred when the model requires increased prediction accuracy and reduction in computation time.

The gain G of each tree is given by

- $G = \frac{1}{2}\left[\frac{T_\alpha(G_{jmL})^2}{H_{jmL}+\lambda} + \frac{T_\alpha(G_{jmR})^2}{H_{jmR}+\lambda} - \frac{T_\alpha(G_{jm})^2}{H_{jm}+\lambda}\right] - \gamma$
- Assign weights to incorrect predictions

Output $G(x) = Sign[\sum \alpha_m G_m(x)]$

The proposed system is designed to achieve high predictive accuracy by leveraging the strengths of both the MSSVM and DSXG-Boost techniques. The selection of mutual dependencies of health-affecting feature limits and the optimization of the recall rate are key factors in improving the overall performance of the system. Based on the predicted classes, the system can provide recommendations for targeted psychological treatment and interventions to protect the public life cycle and ensure the well-being of the community.

3. Results and discussion

The performance of the proposed ensemble learning technique has been extensively evaluated using various metrics, including precision, recall, F1-score, and overall accuracy. The results demonstrate a significant improvement in the prediction accuracy and classification tested in different levels in python framework with public collective log dataset. The proposed DS-XGBoost performance is compared to the existing methods like RF, SVM and ANN, highlighting the effectiveness of the proposed approach in addressing the challenges of work-life imbalance and its impact on public health.

Table 1. Confusion Matrix obtained with proposed classifier

PREDICTED CLASS				
CLASSIFIER	Class	Abnormal	Normal	
RF	HEALTHY	85	10	TRUE CLASS
	STRESS	12	47	
Integration 1				
SVM	HEALTHY	88	7	
	STRESS	12	47	
Integration 1				
ANN	HEALTHY	87	8	
	STRESS	10	49	
Integration 1				
DS XG-BOOST	HEALTHY	88	7	
	STRESS	10	49	

Th testinga nd training validation are carried yb spitting thedatset by getting the ratio under 7:3 pointed by differnet epochs. Table 1shows the Confusion Matrix obtained with proposed classifier The verifactiona nd validaion provess the low tevel loss rate ad higher preidction accuracy to project the proposed performance.

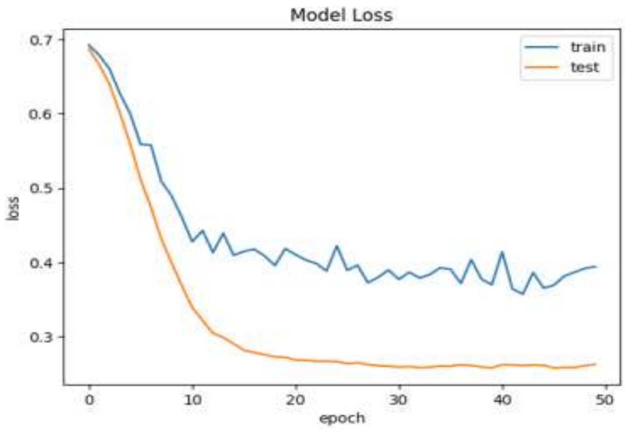

Figure 2. Loss model for training and testing

The figure 2 illustrates the proposed loss performance graph with various epochs. The proposed system obtained a testing loss result of 0.3 and a training loss result of 0.4.

Table 2. Comparison of proposed classification performance

No. of data / methods	RF	SVM	ANN	DS-XGBoost
250	77.3	82.4	92.1	94.2
500	79.2	85.6	93.6	95.3
1000	83.7	87.2	94.7	96.1
1500	85.1	88.9	96.1	97.8

The table 2 shows a comparison of the proposed method DS-XGBoost with the existing methods of RF, SVM, and ANN. The performance level is tested under various counts of microscopic images, such as 250, 500, 1000, and 1500. In all strategy iterations, the proposed shows higher performance than prior existing methods.

Table 3. Classification Accuracy Performance Evaluation

Methods	Sensitivity	Specificity	Precision	Recall	F1 measure
RF	82.31%	82.73%	87.22%	84.23%	88.46%
SVM	84.56%	84.61%	90.18%	86.11%	91.39%
ANN	87.64%	89.79%	91.23%	88.12%	92.17%
DS-XGBoost	90.28%	92.31%	93.46%	93.18%	95.4%

The comparison of the proposed approach with other techniques is made, and the outcomes are presented in Table 2. These outcomes reveal the good performance of the optimized DS-XGBoost algorithm obtained an accuracy result of 95.4%. Following that, the RF result is 88.46%. In contrast, SVM and ANN got accuracy performance of 91.39% and 92.17%, respectively, lower than optimized proposed system.

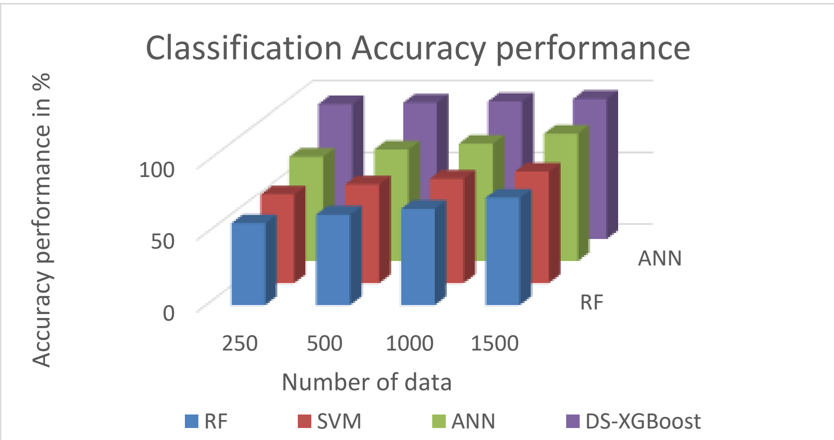

Figure 3. Impact of proposed classification accuracy

Analysis and performance of the proposed DS-XGBoost system accuracy is shown in the above figure. Figure 3 shows the Impact of proposed classification accuracy. The projected DS-XGBoost system proves a higher Stress level detection accuracy, up to 97.8 %, compared to the other methods. The DS-XGBoost unit creates more attention by finding the threads by covering sustainable feature limits. As with the prior methods, RF attains 75.6 %, SVM achieves 78.4 %, and ANN achieves 91.4 % high

4. Conclusion and future scope

The proposed system, which integrates MSSVM and DSXG-Boost, represents a significant advancement in the field of public health prediction. By optimizing ensemble learning techniques, the system can enhance the accuracy of predicting health threats and risks, enabling more effective and proactive interventions. The systematic approach, from data collection and preprocessing to feature selection and classification upto 97.8 % high, ensures a robust and comprehensive solution for addressing the challenges in public health prediction. The implementation of this proposed system can contribute to the continuous improvement of public health outcomes and the overall well-being of the community.

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