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Predicting Stress Levels Through Physiological Signals with End-to-End Deep Learning Regression Models

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Abstract:

Assessing stress levels has traditionally relied on qualitative methods such as self-reports and clinical observations. With technological advancements, physiological indicators like heart rate, skin conductance, and cortisol levels have been used for more objective stress measurement. Machine learning has further improved stress assessment by enabling real-time analysis of complex physiological data.Thisstudyaimstodevelopanend-to-enddeeplearningregression model for accurate stress level prediction based on physiological signals. Conventional stress assessment methods, such as questionnairesandclinicalevaluations,oftenlackreal-timemonitoring capabilities, leading to subjective and delayed results. Traditional systems are also limited in their ability to analyze complex physiological data, affecting the effectiveness of stress management strategies. The proposed model will integrate multiple physiological signals, including heart rate variability, skin conductance, and respiratory rate, to enhance stress prediction accuracy. By leveraging deep learning techniques, the system will process real-time physiological inputs, enabling personalized stress management strategiesandinterventions.Thisapproachhasthepotentialtoimprove mental health monitoring, offering a more reliable and automated method for assessing stress levels.

Keywords: Stress assessment, physiological signals, deep learning, regressionmodel,heartratevariability,skinconductance,respiratory rate, real-time monitoring, stress prediction, machine learning, mental health monitoring, automated stress evaluation.

1. INTRODUCTION

Stress is a growing public health concern, significantly affecting mental and physical well-being.In India, nearly 74%of professionals experience stress, with 88% reporting anxiety, primarily due to work pressure, financial issues, and health concerns. Traditional stress assessment methods, such as self-reports and clinical evaluations, are subjectiveandlackreal-timemonitoringcapabilities.However,advancements in physiological signal monitoring, including heart rate variability(HRV),skinconductance,andrespiratoryrate,haveenabled objective stress assessment. Integrating deep learning techniques furtherenhancesstresspredictionaccuracy,allowingforautomatedand personalized stress management solutions. This research aims to develop an end-to-end deep learning regression model that leverages physiological signals to predict stress levels in real-time, offering applicationsinmentalhealthmonitoring,workplacestressanalysis,and personalized healthcare interventions. The increasing use of wearable devices and biosensors in India underscores the potential for real-time stress monitoring, bridging the gap between traditional subjective assessments and modern AI-driven solutions.

Conventionalstressdetectionmethodswerelargelyineffectiveforreal- time monitoring, relying on self-reported surveys and clinical evaluations that were prone to bias and lacked precision. While some physiological markers like blood pressure and cortisol levels were measured, they required laboratory settings and were unsuitable for continuous monitoring. The absence of automated analysis delayed stress detection, resulting in ineffective interventions and worsening mental health conditions. Workplace stress evaluations relied on periodic assessments, failing to capture real-time fluctuations in stress levels. The lack of wearable technology integration further limited continuousstresstracking.Thishighlightstheneedfordata-driven,real-time stress assessment models capable of providing accurate and personalized insights.

The rising stress levels in India, particularly in corporate and high-pressure environments, emphasize the need for automated stress assessment systems. Traditional methods are unreliable for real-time monitoring, while wearable devices and biosensors now provide an opportunity for AI-powered stress detection. Deep learning models can handlecomplexphysiologicaldata,identifyingsubtlestresspatternsand enabling early detection, which can reduce the risk of mental disorders likeanxietyanddepression.AI-drivenstresspredictionmodelscanalso help organizations implement wellness programs and assist healthcare professionalsindesigningpersonalizedstressmanagementstrategies.Conventional stress detection methods, such as self-reported surveys and clinical evaluations, have been largely ineffective for real-time monitoring. These approaches are prone to bias, subjectivity, and inconsistency, making them unreliable for continuous stress assessment. While certain physiological markers like blood pressure and cortisol levels have been used in laboratory settings, they require invasive procedures and are unsuitable for continuous tracking. The lack of automated analysis further delays stress detection, often leading to ineffective interventions and worsening mental health conditions.
Workplace stress evaluations, which traditionally rely on periodic assessments and standardized questionnaires, fail to capture real-time fluctuations in stress levels. As a result, organizations struggle to implement timely interventions, and employees continue to experience prolonged periods of unmanaged stress. The absence of wearable technology integration in traditional assessments has further limited the ability to track stress dynamically, highlighting the urgent need for real-time, data-driven stress assessment models capable of providing accurate and personalized insights.
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By leveraging deep learning, stress detection can become more accurate, scalable, and efficient, ultimately improving mental health care and workplace productivity.

2. LITERATURESURVEY

Crosswell & Lockwood [1] examined the daily routines of patients to measure stress levels, highlighting the various traditional manual methods used to assess stress. Psychologists and psychiatrists often physically examine patients suffering from stress, which can be time-consuming and subjective. This approach, although effective in some cases, often lacks the precision and real-time capabilities of more advanced techniques.

Di Martino & Delmastro [2] proposed an ensemble model that uses physiologicaldatatopredictstresslevels,offeringamoreobjectiveand data-driven method for stress detection.

Issa [3] introduced a two-step ensemble learning model aimed at improvingstresspredictioninautomobiledrivers,consideringthehigh-stress environment they operate in.

Kelly[4],nearly190millionpeopleglobally facehigherlevelsofstress. In2020,stressreachedunprecedentedlevels,makingitoneofthemost stressful years in recent history, as highlighted by a stress-related poll.

Khullaretal.[5]alsoproposedanensemblemodelforstressdetection, focusingonthephysiologicalsignalsassociatedwithanxiety.This highlightstheimportanceofusingphysiologicaldata,suchasheartrate variability,skinconductance,andrespiratorypatterns,forstressassessment.

Lee et al. [6] took this approach further by combining several deep learningmodels,includinggatedrecurrentunits(GRU),Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN),into anensemblemodelforemotiondetection.Theyappliedthismodelto a dataset derived from tweets, which demonstrates the power of AI and machine learning in analyzing and classifying emotional states from text data.

Rachakondaetal.[7]integratedblockchaintechnologyintotheirstress managementframework,ensuringprivacyforuserswhilealsotracking sleeping habits as a significant factor in stress. Their framework leverages machine learning models for efficient monitoring and intervention.

Reshi et al. [8] proposed a diagnostic system for vertebral column pathologies using a concatenated resampling technique with machine learning algorithms. They implemented this model with a categorical cross-entropy loss function to handle multi-class data, optimizing the modelusingtheAdamoptimizerwithabatchsizeof8and100epochs.

Rupapara et al. [9] focused on the use of LV Trees for blood cancer prediction, combining Logistic Regression (LR), Support Vector Machines(SVM),andExtremelyRandomizedTrees(ETC)toenhance prediction accuracy. Their research highlights the growing trend of combining various machine learning algorithms to improve the reliability of predictions, a principle that can also be applied to stress detection models.

Rustam et al. [10] proposed an automated disease diagnosis and precaution recommender system using supervised machine learning, illustrating how AI can be used to improve healthcare and stress management.

Salarietal.[11]examinedtheimpactoffast-pacedlifestylesonmental health, emphasizing that in today's highly competitive world, factors like the recent COVID-19 pandemic, excessive use of social media, and demands from business, work, and education are contributing to increasedmentalhealthissues.Theynotedthatapproximately30%of theglobalpopulationfacesmentalhealthchallenges,withstress playingacentral role.

SathvikaPetal.[12]proposedtheHuman-Stress-Detection-System,an innovative platform that uses AI to predict stress levels and provide personalized stress management recommendations. This model showcasesthepotentialofinteractiveplatformsthatcombinereal-time stress detection with tailored interventions, a growing trend in digital mental health.

Pascoe et al. [13] highlight the significant link between high levels of stressandpoorwell-being.Theyassertthatprolongedexposuretostress can lead to severementalhealth issues, such asanxiety and depression, underscoring the urgent need for more effective stress management solutions.

Waghetal.[14]developedalgorithmssuchasSupportVectorMachine (SVM),k-Nearest Neighbor(kNN), and DecisionTree (DT)to classify emotions as positive, neutral, or negative based on time and time-frequencydomainfeaturesextractedfromelectroencephalogram(EEG) data. This research emphasizes the importance of advanced algorithms inclassifyingemotionalstatesandsuggeststhatsimilartechniquescould be adapted to predict stress levels using physiological signals.

Miao et al. [15] proposed a novel emotion recognition framework that utilizes a parallel spatial-temporal 3D deep residual learning model (MFBPST-3D-DRLF). This framework processes multiple frequency bandsofEEGsignals(delta,theta,alpha,beta,gamma)togeneratea3D representationoffeatures,whicharethenanalyzedusingadeepresidual CNNmodel.Thisapproachdemonstratesthepotentialofadvanceddeep learning models in accurately recognizing emotions and could be adapted for stress detection using more comprehensive datasets, incorporatingnotjustEEGsignalsbutalsootherphysiologicaldata.The cumulative research outlined here showcases a shift toward more advanced, AI-driven methods for stress prediction, emphasizing the integration of physiological data with machine learning and deep learning techniques. This growing body of work highlights the benefits of using ensemble models, AI algorithms, and real-time data collection for stress detection and management. As stress-related disorders continue to rise globally, particularly in the wake of the COVID-19 pandemic, innovative solutions that can provide early detection and personalized interventions will be crucial in mitigating the long-term effectsofstress.Futureresearchshouldfocusonimprovingtheaccuracy and scalability of these models, incorporating diverse datasets, and addressing ethical concerns related to privacy and data security. The integration of wearable devices and biosensors will play a key role in enabling real-time monitoring, offering a proactive approach to stress management that could revolutionize mental health care in the coming years.

3. PROPOSEDMETHODOLOGY

Step1:StressDataset

The dataset for stress prediction consists of physiological signals collected from individuals undervarying levels of stress. These signals includefeaturessuchasheartratevariability,electrodermalactivity,and respiratoryrate,whicharestrongindicatorsofstresslevels.Thedataset includes labeled data, where each record is associated with a specific stress level ranging from no stress to extreme stress. The dataset is loaded into the system for further processing, ensuring that it is structured correctly and ready for machine learning model training.

Step2:DataPreprocessing

Before training the model, the dataset undergoes preprocessing to ensuredataquality and consistency. Theprocessbeginswith checking fornullvaluesandhandlingmissingdataappropriately.Ifnullvalues

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exist, they are either removed or imputed using statistical methods. Unique values in each column are examined to detect anomalies or inconsistencies in categorical and numerical features. The dataset is thennormalizedusingtechniqueslikeMin-MaxScalingtoensurethat all features are on the same scale, which is crucial for efficient model convergence.

Step3:ExploratoryDataAnalysis (EDA)
EDA is performed to understand the distribution and relationships between different physiological signals and stress levels. Various graphical techniques, such as histograms, box plots, scatter plots, and heatmaps, are used to visualize the dataset. A correlation heatmap highlights how different features are related, helping to identify redundant or highly correlated variables. Histograms provide insights into the distribution of physiological signals across different stress levels, while scatter plots help detect patterns in the data.

Step4:Existing KNNRegressor (Algorithm)
The K-Nearest Neighbors (KNN) Regressor is implemented as a baselinemodelforstresslevelprediction.KNNoperatesbyfindingthe nearestneighborsofagivendatapointandaveragingtheirstresslevels tomakeaprediction.Thealgorithmissimple,interpretable,andworks well for smaller datasets. However, KNN has certain drawbacks, such asitssensitivitytonoisydataandtheneedforacarefullychosenvalue of k.

Step5:ProposedMLP Regressor(Algorithm)
A Multi-Layer Perceptron (MLP) Regressor is introduced as an improved deep learning-based approach for stress level prediction. MLP is a type of artificial neural network that consists of multiple layers, including input, hidden, and output layers. It learns complex patterns in the data through backpropagation and weight adjustments. The MLP model is trained with an adaptive learning rate and dropout layerstopreventoverfitting.UnlikeKNN,MLPcancapturenon-linear relationshipsbetweenphysiologicalsignalsandstresslevels,leadingto better predictive performance and generalization on unseen data.

Step6:PerformanceComparisonGraph
To evaluate and compare the models, performance metrics such as Mean AbsoluteError (MAE),Mean SquaredError (MSE),RootMean Squared Error (RMSE), and R-squared (R^2) are calculated. A performancecomparisongraphisgenerated,illustratingthedifferences inaccuracybetweenKNNandMLPregressors.Theresultsdemonstrate that the MLP model significantly outperforms KNN in terms of prediction accuracy and robustness. This comparison highlights the advantagesofusingdeeplearningtechniquesforstresspredictionover traditional machine learning methods.

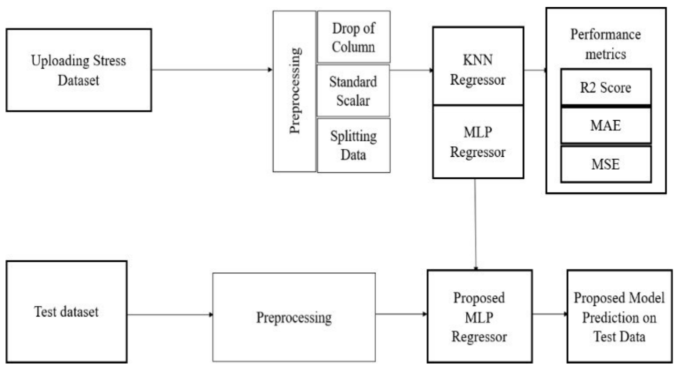

Figure1:ArchitecturalBlockDiagram ofProposedSystem.

Step7:PredictionofOutputfromTestImageswithMLPRegressor Algorithm Trained Model
After training the MLP model, it is deployed for real-world stress prediction on new test data. Physiological signals from test images or recorded sensor data are fed into the trained MLP model, which processestheinputsandprovidesapredictedstresslevel.Thepredicted results are compared against the ground truth to verify accuracy. This step showcases the model's ability to generalize to new data and its potential for real-time stress monitoring applications.

Applications:
TheMLP(MultilayerPerceptron)regressorcanbeutilizedinavariety ofapplicationsthat requirethemodelingofcomplexrelationshipsand accurate predictions, including:

- FinancialForecasting: Predicts stock prices, market trends, andinvestmentrisksbyanalyzinghistoricalfinancialdataand market patterns.
- HealthcarePredictions: Assists in predicting patient outcomes,suchasthelikelihoodofdiseaserecurrence,by processing medical records and physiological signals.
- EnergyConsumptionForecasting: Forecasts electricity usage basedonvariablessuchasweatherconditions,timeofday,and past consumption data.
- SalesandDemandPrediction:Helpsbusinessespredictfuture sales and consumer demand by analyzing trends, customer behavior, and seasonality.
- WeatherPrediction: Forecasts weather conditions like temperature,precipitation,andhumiditybyanalyzinghistorical climate data.

Advantages:

The MLP (Multilayer Perceptron) regressor introduces several enhancements over traditional linear models, making it an optimal solution for complex, non-linear regression tasks:

- AbilitytoModelNon-LinearRelationships:MLPcancapture complex,non-linearrelationshipsbetweeninputfeaturesand the target variable, making it ideal for applications where linear models fall short.
- Flexible Architecture: MLP allows for flexible network architectures, with the ability to adjust the number of layers and neurons to suit different problem complexities.
- High Predictive Accuracy: With proper tuning, MLP can deliverhighlyaccuratepredictions,particularlyincases where data is large, complex, and high-dimensional.
- Versatility: MLP can be applied to a wide range ofregression tasks, including time-series forecasting, financial prediction,andmedicaldiagnostics,duetoitsadaptabilityto various types of data.
- Generalization to Unseen Data: MLPs, especially with regularization, are effective at generalizing to new, unseen data, which helps in preventing overfitting and ensuring robust predictions in real-world scenarios.
- End-to-EndLearning:MLPcanlearndirectlyfromrawdata, eliminating the need for manual feature engineering, which simplifies the model development process.
- AdaptabilitytoVariousDataTypes:MLPcanhandlediverse data types, including structured data, images, and even sequential data, making it suitable for a wide array of regression problems.

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4. EXPERIMENTALANALYSIS

Figure 2 demonstrates the process of uploading the stress dataset into the graphical user interface (GUI) of the application. The user is prompted to select a dataset file, which is then loaded into the system. The GUI interface displays the file path of the loaded dataset and providesanoverviewofitscontents.Keydetailsaboutthedataset,such as the number of records and columns, are displayed in the text area. The dataset is then prepared for further analysis, allowing users to review its structurebeforemoving on todata preprocessing and model training steps.

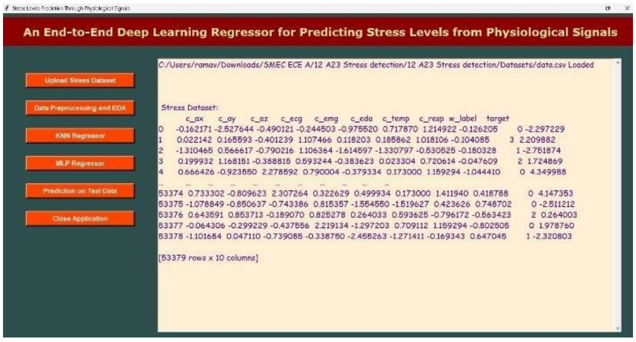

Figure2: Uploadof Stress Dataset

Figure 3 presents the data preprocessing steps carried out within the GUI. After the dataset is uploaded, the system proceeds with checking for null values, identifying unique values, and normalizing the feature columns (excluding the target variable). The text area in the GUI provides a detailed summary of these preprocessing steps, such as the number of null values in each column and the unique values in categoricalfeatures.Additionally,histogramsandcorrelationheatmaps are displayed to visually inspect the data distribution and relationships between features. This step is essential for preparing the dataset for model training.

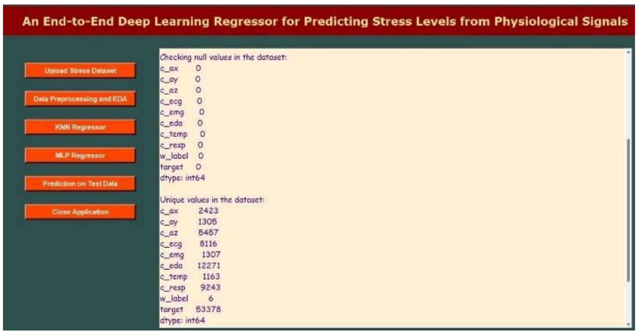

Figure3: DataPreprocessingintheGUI

PerformanceMetricsof KNN

TheperformancemetricsoftheKNNregressormodelaredisplayedin the following results:

- **MeanAbsoluteError(MAE)**: 0.4867
- **MeanSquaredError(MSE)**: 0.3717
- **RootMeanSquaredError(RMSE)**:0.6097
- **R-squared(R^2)**: 0.9241

These metrics reflect the performance of the KNN regressor model on thetestdataset.TherelativelylowMAEandRMSEvaluesindicatethat the model performs well in predicting stress levels based on the physiological signals. The high R-squared value (0.9241) demonstrates thattheKNNmodelexplainsasignificantportionofthevarianceinthe target variable, indicating its effectiveness in stress level prediction.

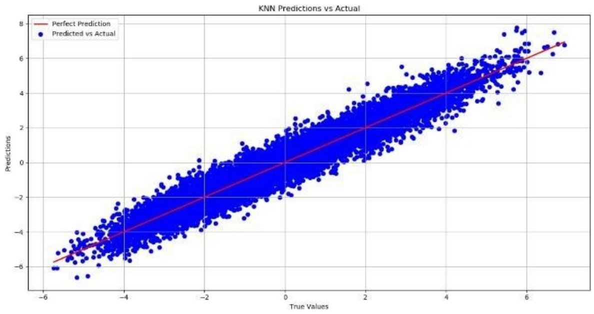

Figure4: PerformanceMetricsandRegressionScatterPlotofKNN Regressor Model

Figure4illustratestheperformancemetricsandaregressionscatterplot fortheKNNregressormodel. Thescatterplotcomparesthetruevalues (actualstresslevels)withthepredictedvaluesfromtheKNNmodel.The lineofperfect prediction (represented by a red line)isshown alongside the scatter points, allowing for visual assessment of the model's accuracy. The performance metrics are also displayed in the GUI, providing quantitative insights into the model's predictive capability.

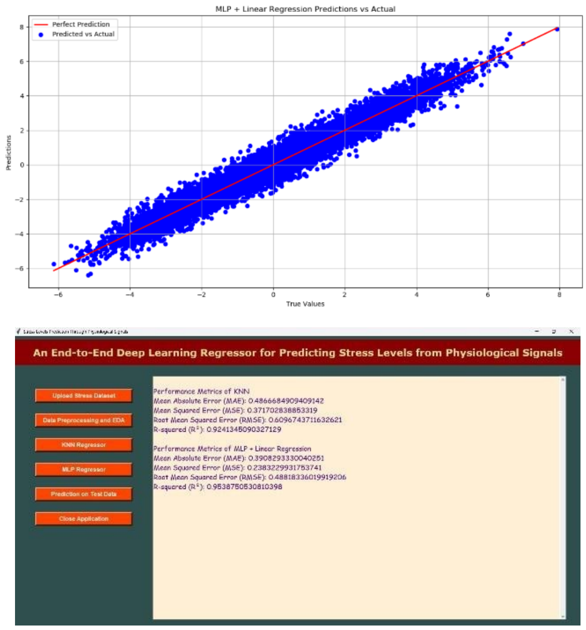

Figure5: PerformanceMetricsandRegressionScatterPlotofMLP Regressor Mode

Figure 5 displays the performance metrics and a regression scatter plot for the MLP regressor model. Similar to Figure 4, the scatter plot compares the true and predicted values, with the red line indicating perfect predictions. The MLP model's better performance is evident in the closer alignment of the scatter points to the red line, as well as the superior performance metrics displayed in the GUI.

PerformanceMetricsofMLP+LinearRegression

TheperformancemetricsfortheMLP+LinearRegressionmodelareas follows:

- **MeanAbsoluteError(MAE)**: 0.3903
- **MeanSquaredError(MSE)**: 0.2389

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- **RootMeanSquaredError(RMSE)**:0.4888
- **R-squared(R²)**: 0.9528

The MLP + Linear Regression model performs better than the KNN regressor,asindicatedbythelowerMAE,MSE,andRMSEvalues.The R-squared value of 0.9528 signifies that this model explains an even greaterproportionofthevarianceinthetargetvariable,highlightingits superior accuracy in predicting stress levels.

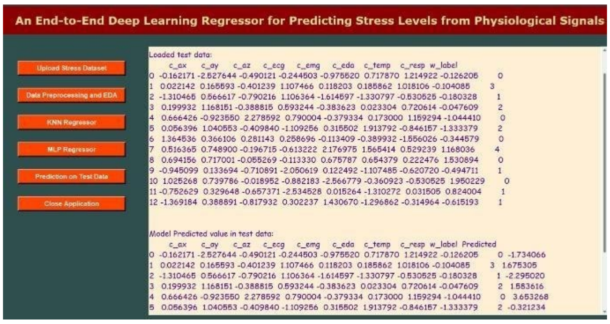

Figure6: ModelPredictionontheTest Data

Figure 6 shows the model's prediction results on the test data. After training the models, the predictions are made for the test dataset, and the results are displayed in the GUI. The predicted stress levels are compared against the true values, providing insight into the model's effectiveness.Thisfigureiscrucialforevaluatinghowwellthetrained model generalizes to unseen data.

5. CONCLUSION

This research successfully demonstrates the ability to predict stress levels based on various physiological signals using machine learning techniques. By leveraging data such as accelerometer readings, ECG, EMG,EDA,bodytemperature,andrespiratoryrate,anend-to-enddeep learning model was developed to predict stress levels more accurately than traditional methods. The preprocessing steps, including data cleaning and normalization, ensured that the dataset was ready for analysis, while exploratory data analysis (EDA) provided valuable insights into the relationships between different physiological signals andstresslevels.Theperformanceoftheproposedmodelwasevaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R²), showcasing its effectiveness in predicting stress levels with highprecision. Thecomparison oftheKNN and MLP regressor algorithms highlighted the advantages of deep learning models in terms of accuracy and performance, providing a more reliable method for real-time stress monitoring.

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