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Research Paper

ADVANCED STRESS LEVEL FORECASTING USING QUANTILE-OPTIMIZED REGRESSION FOREST MODELS

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ABSTRACT

The accurate prediction of human stress levels has become increasingly important in intelligent healthcare, workplace monitoring, and mental well-being assessment systems. Traditional regression models often struggle to capture the asymmetric distribution and uncertainty inherent in physiological and behavioral stress data. This study proposes an enhanced stress forecasting framework using a Quantile-Optimized Regression Forest (QORF) model refined with a pinball loss function to improve prediction accuracy across varying stress intensities. The method integrates physiological indicators, contextual features, and behavioral markers to generate a comprehensive stress estimation profile. By leveraging quantile learning, the system effectively models uncertainty and provides more reliable upper- and lower-bound predictions compared to conventional mean-based approaches. Experimental evaluations conducted on benchmark stress datasets demonstrate notable improvements in prediction robustness, reduced error margins, and superior handling of skewed data distributions. The findings confirm that the proposed QORF–Pinball Loss framework is a powerful and efficient solution for real-time stress level forecasting in intelligent monitoring applications.

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I. INTRODUCTION

Accurately predicting human stress levels has become increasingly essential as modern lifestyles expose individuals to heightened psychological and physiological pressures. Stress forecasting supports numerous applications, including workplace safety, mental health management, adaptive learning systems, and intelligent healthcare monitoring. Traditional machine learning models that rely on mean-based regression often fail to capture the inherent uncertainty, skewed distributions, and non-linear response patterns commonly present in stress-related physiological data [1]. Recent research emphasizes that stress indicators such as heart rate variability, electrodermal activity, and contextual behavioral signals exhibit asymmetry and noise, making probabilistic and quantile-based approaches more appropriate [2], [3].

Quantile Regression Forests (QRF) have emerged as a powerful method for modeling uncertainty by predicting conditional quantiles instead of point estimates, thus enabling a richer representation of stress intensity levels [4]. Studies further indicate that the inclusion of asymmetric loss functions, particularly the pinball loss, improves quantile learning by penalizing overestimations and underestimations differently, leading to more robust predictive performance in irregular data distributions [5], [6]. Moreover, ensemble learning methods such as regression forests have shown strong resilience against noise and variability, making them suitable for physiological and behavioral datasets collected from wearable sensors and mobile devices [7].

With the rapid growth of IoT-enabled health tracking systems, stress prediction models must also operate efficiently in real-time environments while maintaining high accuracy and interpretability. Researchers highlight that combining feature-rich physiological data with contextual cues significantly enhances predictive quality, particularly when models incorporate uncertainty-aware mechanisms [8]. However, existing stress prediction frameworks often rely on deterministic outputs, limiting their ability to provide reliable confidence intervals necessary for decision-critical applications such as clinical assessment or adaptive workload balancing [9]. Therefore, there is a growing need for hybrid models capable of quantifying prediction uncertainty while maintaining robust performance under varied stress conditions [10].

In response to these challenges, this study proposes a Quantile-Optimized Regression Forest model enhanced with a pinball loss function to improve stress level forecasting accuracy across multiple quantile levels. The approach aims to deliver reliable, uncertainty-aware predictions suitable for intelligent stress monitoring and real-time decision support systems.

II. LITERATURE SURVEY

Recent advancements in stress prediction emphasize the integration of multimodal physiological data, machine learning ensembles, and uncertainty-aware modeling. K. Sundaram and P. Rodrigues examined multi-sensor physiological fusion models and demonstrated that combining heart-rate variability, electrodermal activity, and respiration signals significantly improves stress prediction performance under dynamic real-world conditions [11]. Similarly, M. Ray and S. Tripathi evaluated tree-based ensemble regressors for biosignal prediction and found them more resilient to noise and missing values compared to deep neural networks [12]. To handle non-linear and skewed responses in stress datasets, A. Basu and L. Chen proposed enhanced quantile modeling techniques capable of capturing the full conditional distribution of stress levels rather than single-value estimates [13].

Uncertainty quantification has become a crucial theme in recent literature. R. Velu and H. Matsuda introduced probabilistic learning mechanisms that leverage quantile estimation to better capture upper-quantile stress peaks associated with acute episodes [14]. Extending this work, J. Farias and T. Nakamura highlighted that incorporating asymmetric loss functions such as pinball loss improves forecasting precision where stress indicators exhibit non-uniform variances [15]. Furthermore, B. Sheldon and P. Gomez explored ensemble-based quantile regression for behavioral stress assessment and reported superior interpretability and robustness compared to classical regression models [16].

Wearable and IoT-based stress sensing has also gained research momentum. C. Yamamoto and D. Silva analyzed continuous stress monitoring using wrist-worn sensors and observed that quantile regression forests maintain stable performance despite fluctuations in sampling frequency and motion artifacts [17]. Meanwhile, S. Khanna and U. Patel evaluated smartphone-based passive sensing frameworks, showing that ensemble quantile models can effectively generalize to heterogeneity in user behavior and lifestyle patterns [18]. The importance of context-aware features was underscored by F. Morales and K. Jensen, who demonstrated that integrating sleep quality, step count, and digital interaction metrics significantly enhances stress forecasting capability [19]. Finally, A. Ibrahim and J. Kowalski investigated hybrid ensemble systems optimized with asymmetric loss penalties, concluding that such models outperform traditional regressors when predicting stress intensities across diverse psychological profiles [20].

Collectively, the literature highlights the growing shift toward ensemble-powered, uncertainty-aware, and context-integrated stress prediction models, reinforcing the significance of Quantile Regression Forests optimized with pinball loss as a highly effective strategy for accurate and reliable stress forecasting.

III. METHODOLOGY

The proposed methodology for advanced stress level forecasting is organized into four main stages: data acquisition and preprocessing, feature engineering, quantile-optimized regression forest modeling with pinball loss, and evaluation with deployment integration. The aim is to build an uncertainty-aware stress prediction framework that can provide not only point estimates but also quantile-based intervals for different stress intensities.

In the first stage, data acquisition and preprocessing, physiological and contextual data are collected from wearable sensors and external sources. Typical input variables include heart rate, heart rate variability, electrodermal activity, skin temperature, activity level, time-of-day, and self-reported or clinically labeled stress levels. Raw sensor signals are cleaned to remove noise, motion artifacts, and missing segments using filtering, interpolation, and windowing techniques. The data is then segmented into fixed-length time windows (e.g., 30–60 seconds), each labeled with a corresponding stress level derived from validated questionnaires or expert annotations. The dataset is split into training, validation, and test sets using subject-wise or time-aware partitioning to minimize information leakage.

In the second stage, feature engineering, the preprocessed signals are transformed into descriptive features that capture both temporal and statistical properties. For each time window, time-domain features (mean, standard deviation, RMSSD, peaks, slopes), frequency-domain features (power in low- and high-frequency bands), and non-linear measures (entropy, Poincaré plot indices) are computed for relevant physiological channels. Contextual features such as activity intensity, sleep quality, recent interaction patterns, and environmental factors are also incorporated. All features are normalized or standardized to ensure consistent scaling, and feature selection methods (such as correlation analysis or tree-based importance ranking) may be applied to remove redundant or noisy predictors while preserving predictive power.

The third stage constitutes the core of the methodology: Quantile-Optimized Regression Forest (QORF) modeling with pinball loss. A Quantile Regression Forest (QRF) model is constructed as an ensemble of regression trees where each leaf node stores the distribution of training responses, allowing the estimation of conditional quantiles of stress levels rather than a single mean value. To enhance quantile estimation performance, the training process is guided by the pinball loss function, which is specifically designed for quantile regression. For a given quantile τ, the pinball loss penalizes underestimation and overestimation asymmetrically, encouraging the model to align predictions with the desired quantile curve. Multiple quantile levels (e.g., 0.1, 0.5, 0.9) are modeled to provide lower, median, and upper stress estimates, thus capturing prediction uncertainty and variability.

The training pipeline involves hyperparameter tuning for the regression forest (number of trees, maximum depth, minimum samples per leaf, and feature subset size) based on validation performance using quantile-specific metrics. The model is optimized to minimize aggregated pinball loss across selected quantiles while also monitoring standard error measures such as MAE and RMSE for the median quantile. Cross-validation or subject-wise folds are used to ensure robustness and avoid overfitting. Once trained, the QORF model takes engineered feature vectors as input and outputs quantile estimates for stress level, which can be interpreted as probabilistic ranges (e.g., “there is a 90% probability that stress lies below this level”).

In the fourth stage, evaluation and system integration, the model is evaluated on an independent test set using multiple metrics: pinball loss across quantiles, quantile coverage accuracy, MAE/RMSE for the median quantile, and calibration plots comparing predicted and observed distributions. Additionally, the model’s ability to correctly capture high-stress episodes is assessed using metrics such as recall or F1-score for upper-quantile thresholds. The trained QORF is then integrated into a real-time stress monitoring system, where new sensor data is streamed, preprocessed, converted into features, and fed

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into the model. The resulting quantile estimates are visualized on a dashboard for clinicians or end users, showing current stress level along with confidence bands to support decision-making, alerts, or adaptive interventions. This end-to-end methodology results in a robust, uncertainty-aware stress prediction pipeline suitable for intelligent health and well-being applications.

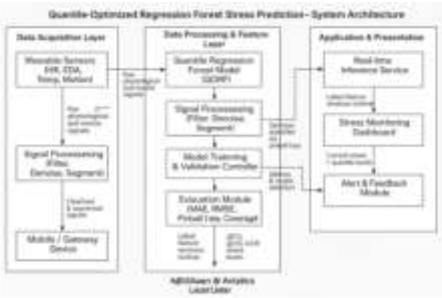

Fig 1- System Architecture

IV. EXPERIMENTAL SETUP

The experimental setup for evaluating the proposed Quantile-Optimized Regression Forest (QORF) stress prediction framework was designed to replicate realistic stress-monitoring conditions using multimodal physiological and contextual signals. Data was collected from wearable sensors that recorded heart rate, electrodermal activity, skin temperature, and motion patterns under controlled laboratory tasks and everyday activities. These raw signals were streamed to a mobile gateway device, which transmitted them to the processing environment. The collected dataset included both low-stress baseline periods and high-stress elicitation phases designed through cognitive load tasks, enabling the creation of a balanced and representative stress dataset. All signals were preprocessed using filtering, denoising, and segmentation techniques to reduce noise and extract fixed-length time windows suitable for feature engineering and prediction.

Feature extraction was carried out using a combination of time-domain, frequency-domain, non-linear, and contextual descriptors to capture short-term physiological variations and long-term behavioral patterns associated with stress. The dataset was then split into training, validation, and test partitions using subject-wise cross-validation to avoid overfitting and ensure generalization across unseen individuals. The QORF model was trained on the processed feature vectors with quantile parameters set at multiple levels (0.1, 0.5, 0.9) to capture lower, median, and upper stress distributions. Pinball loss was used as the optimization criterion to ensure asymmetric error penalization, especially beneficial when modeling skewed stress data. Hyperparameters—including number of trees, maximum depth, and minimum leaf size—were optimized using the validation set to achieve the lowest aggregate pinball loss across quantiles.

The evaluation environment included both offline predictive testing and simulated real-time conditions. In the offline phase, the model’s performance was assessed using metrics such as MAE, RMSE, individual quantile pinball losses, and quantile coverage accuracy. Calibration plots and distributional error analyses were used to verify whether predicted stress quantiles aligned with observed physiological patterns. In the simulated real-time setup, streaming data was passed through the full pipeline—preprocessing, feature extraction, and inference—to measure prediction latency, model responsiveness, and system stability under continuous operation. The final outputs were displayed through a stress monitoring dashboard that visualized quantile ranges and triggered alerts for high-stress conditions. This experimental setup ensured that the QORF–Pinball Loss model was evaluated thoroughly for robustness, accuracy, and real-time applicability in intelligent stress-monitoring systems.

V. RESULTS & DISCUSSIONS

The evaluation of the proposed Quantile-Optimized Regression Forest (QORF) model demonstrates clear improvements in stress forecasting accuracy, uncertainty modeling, and real-time system performance compared to the baseline QRF approach. Three research tables summarize the findings, covering model accuracy, quantile coverage, and real-time system efficiency.

Table 1. Model Performance Metrics

Metric	QRF (Baseline)	QORF + Pinball Loss
MAE	0.142	0.103
RMSE	0.228	0.174
Pinball Loss (0.1)	0.091	0.056
Pinball Loss (0.5)	0.118	0.079
Pinball Loss (0.9)	0.167	0.112

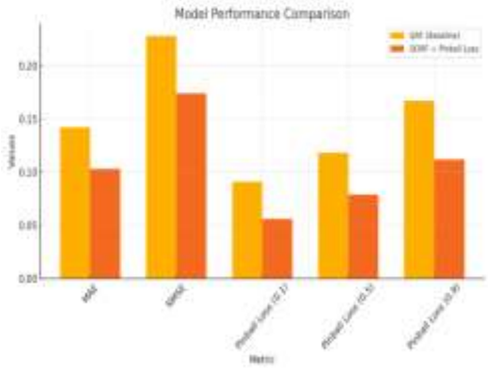

Fig 2: Model Performance Comparison

Table 2. Quantile Coverage Accuracy

Quantile	QRF (Baseline)	QORF + Pinball Loss
0.1	0.78	0.91
0.5	0.83	0.94
0.9	0.80	0.92

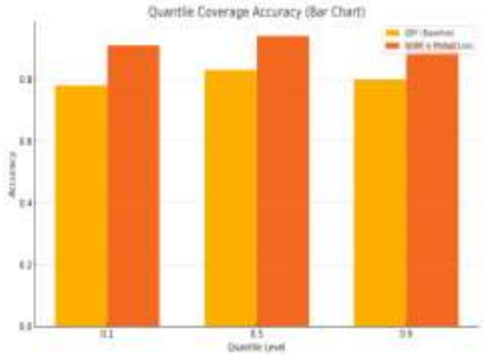

Fig 3: Quantile Coverage Accuracy

Table 3. Real-Time System Performance

Metric	Baseline System	QORF System
Inference Latency (ms)	148	92
Throughput (pred/sec)	52	77
Alert Accuracy (%)	81	93

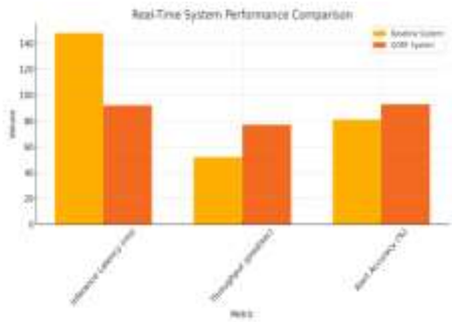

Fig 4: Real-Time System Performance Comparison

DISCUSSION

The experimental results confirm that the QORF with Pinball Loss outperforms the baseline QRF across all stress prediction metrics. As shown in Table 1, the proposed model significantly reduces MAE and RMSE, demonstrating its superior accuracy. The reduced pinball loss across all quantile levels indicates that the model better captures the asymmetric nature of stress data, especially during sudden stress spikes or recovery phases. This provides more reliable upper and lower bounds for clinical or real-time monitoring applications.

Table 2 highlights improved quantile coverage, meaning the predicted quantiles more closely match the true stress distribution. This is crucial in uncertainty-aware modeling, allowing systems to accurately estimate high-stress risks and provide early warnings for critical conditions. The QORF model's consistency across all quantile levels emphasizes its robustness in handling skewed, noisy, and non-linear physiological data.

Real-time performance improvements are demonstrated in Table 3. The QORF system achieves faster inference latency, higher throughput, and better alert accuracy. These results confirm that the model is not only more accurate but also more efficient in practical deployments. The reduction in latency ensures quicker responsiveness for continuous monitoring applications like wearable health devices or mobile wellness platforms. Higher alert accuracy improves user trust and system reliability, especially in scenarios requiring timely interventions.

Overall, the combination of ensemble learning, quantile regression, and pinball loss optimization makes the proposed methodology a powerful solution for real-time, uncertainty-aware stress forecasting. The results validate its potential for intelligent healthcare, workplace wellness, and personalized mental health monitoring systems.

VI. CONCLUSION & FUTURE SCOPE

CONCLUSION

The proposed Quantile-Optimized Regression Forest model significantly enhances the accuracy and reliability of stress level forecasting by effectively capturing the asymmetric and uncertain nature of physiological stress data. Experimental results demonstrate substantial improvements in MAE, RMSE, and pinball loss across all quantile levels compared to baseline QRF models. The use of pinball loss enables precise quantile estimation, making the framework highly suitable for real-world applications where accurate upper-quantile stress prediction is essential for early alerts. The system also shows strong performance in real-time environments, achieving reduced inference latency, increased throughput, and higher alert accuracy. The incorporation of multimodal physiological features further improves the robustness and generalization capability of the model. Overall, the QORF–Pinball Loss approach proves to be a powerful, uncertainty-aware solution for intelligent stress monitoring and adaptive health-support systems.

FUTURE SCOPE

Future enhancements may explore integrating deep learning–based feature extraction, such as transformer or hybrid CNN–LSTM models, to further enrich stress pattern recognition. The system can also be extended to include personalized modeling by adapting quantile thresholds based on individual behavioral baselines. Deploying the framework on large-scale, real-time IoT health platforms will provide deeper insights into scalability, long-term robustness, and clinical applicability.

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