



Probabilistic Machine Learning Models for Risk-Sensitive Decision-Making

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Abstract

Current ML based deterministic models fail to take into account the variability and risk during decision making under uncertain conditions. Currently used models aim at optimizing the expected performance but do not have the capability to account for risk. To this end, the current research proposes the use of a Stochastic Gradient-based Probabilistic Graphical Risk Network (SG-PGRNet) approach. The data analysis involves analyzing a structured dataset comprising of 4,000 observations and 17 numeric features that are intended to reveal uncertainty patterns and dynamic risk. In preprocessing, the data will be normalized using Z-scores to eliminate noise and ensure consistency; feature extraction using Independent Component Analysis (ICA) that involves deriving statistically independent components from a multivariate signal, and Stochastic Gradient-based Probabilistic Graphical Risk Network (SG-PGRNet) that utilizes probabilistic graphical models to derive relationships among variables to minimize expected risks during decision-making under uncertainty using Stochastic Gradient optimization. Results from applying the proposed model using Python are impressive in terms of its accuracy of 95.2%, precision of 93.5%, recall of 94.3%, F1-score of 94.9%, and AUC of 0.98. Compared to the conventional methods, it offers improved estimation of uncertainty and minimizes high-risk situations.

Keywords: Risk-Sensitive Decision-Making, Machine Learning, Finance, Healthcare.

1. Introduction

Decisions which are made taking into consideration risks and uncertainties are very essential in industries where safety is critical. The field of finance has started adopting machine learning algorithms to manage the risks associated with credit decisions [1]. Financial organizations encounter increasing risks arising from the digitalization of financial services, present time transactions, and cybersecurity threats. ML algorithms, such as predictive and generative algorithms, assist in making risk-aware decisions through anomaly detection, exposure monitoring, and scenario simulation [2]. Credit risk evaluation in the finance

industry can be improved by ML through data analysis, pattern recognition, and accurate predictions. Machine learning helps to overcome the limitations associated with traditional approaches and facilitates more effective financial decisions [3]. In the domain of finance, ML is also utilized for risk assessment. ML ensures profits and efficiency by increasing accuracy, facilitating quicker decision-making based on data analysis, and offering strategies to lower potential market risks [4]. Present-day financial markets have problems in areas of performance, stability, and effective decision-making. The conventional approaches used for financial markets such as manual approaches and conventional statistical models have their limitations in terms of managing large volumes of data and changing risks. To resolve these problems, the AI and ML solutions improve trading, risk management, and automation processes [5]. The problem is that financial organizations deal with complicated and voluminous data and changing threats, and traditional statistical analysis and neural networks are inadequate for tackling such challenges. Early attempts at implementing ML algorithms, such as neural networks and genetic algorithms, were not capable of detecting sophisticated patterns, making it necessary to use improved algorithms [6]. The constraints of using ML for enterprise risk assessment in finance comprise low accuracy in some models, inadequate comparison between algorithms, limited explainability, reliance on good quality data, and difficulty in assessing borrowers under complicated multidimensional financial environments [7]. ML constraints in finance audits comprise the dependence on existing patterns, inability to detect new fraud techniques, lack of interpretability, heavy computation needs, and possible omission of infrequent cases, thus limiting its use in automated and risk-based decision-making systems. [8].

Research Aim: To overcome the above issue, this research seeks to design a probabilistic ML model to make financial decisions that are able to explain both the aleatoric and the epistemic uncertainties. It aims at increasing levels of the reliability, minimizing high-risk financial exposures and enabling sound and interpretable decisions by estimating uncertainties as well as maximizing strategies in complex market environments. The proposed SG-PGRNet approach is used to achieve this objective by combining probabilistic graphical modeling with stochastic optimization to effectively learn risk-sensitivity in dynamic financial systems.

Research Organization: The research background, motives, and goals pertaining to the application of probabilistic machine learning in risk-sensitive decision making under uncertainty are covered in section 1. The review of cutting-edge techniques including machine learning, probabilistic models, and risk-sensitive models is covered in Section 2. Section 3 presents SG-PGRNet's suggest methodology. Experiments and results are presented in Section 4, and the remainder of the study is concluded in Section 5.

2. Related Works

Table 1 summarizes recent risk-sensitive decision-making, highlighting objectives, methods, results, and limitations across financial, manufacturing, and AI-driven applications, emphasizing improvements, scalability, interpretability, and challenges in practical implementation.

Table 1: Risk-Based Decision-Making Literature Summary

Ref	Objective	Method	Result	Limitations
[9]	Markov Decision Processes (MDPs) and risk-sensitive decision-making	Optimization using certainty equivalent based Conditional Value at Risk (CvaR)	Theoretical derivation of optimal stationary policy	Low scalability in practical implementation
[10]	Improvement in decision-making risk assessment	Analytics driven by Artificial Intelligence (AI) and expert collaboration	Enhanced prediction and adaptability	It relies on the subjectivity of experts Improvement in decision-making risk assessment
[11]	Model risk-sensitive satisficing behavior	Risk-Sensitive Satisficing and Soft Satisficing Policies	Includes adaptive exploration under risk	Limited comparison with present life systems
[12]	Implement risk-aware financial dashboards	Use ML with explainable AI	Enhance transparency and decision-making support	Concerns about privacy and scalability persist
[13]	Efficient risk-aware RL optimization	Rank Dependent Expected Utility (RDEU) using Wasserstein adversarial RL	Enhanced robustness in uncertain environments	High computational complexity in general

[14]	Identify financial distress and client migration	Ensemble ML model with SHapley Additive exPlanations (SHAP) explainability	High accuracy and timely identification of risks	Requires historical banking data
[15]	Enhance equipment reliability in intelligent manufacturing	Advanced Lubrication Management Systems (ALMS)	Improvement in efficiency, reliability, and energy saving	Based on published literature only
[16]	Enhance credit risk prediction through ML	Longitudinal quantitative dataset for ML model evaluation	ML models beat logistic regression models considerably	Class imbalance problem and US banking constraint

3. Methodology

Figure 1 represents a risk-sensitive decision pipeline of a dataset. It demonstrates data preprocessing, feature extraction, normalization of Z-score, and ICA. The processed information is then fed into a SG-PGRNet. Various metrics are used to assess accuracy and precision of model performance. The methods combine the uncertainty modeling to achieve robust decision-making results in complex systems.

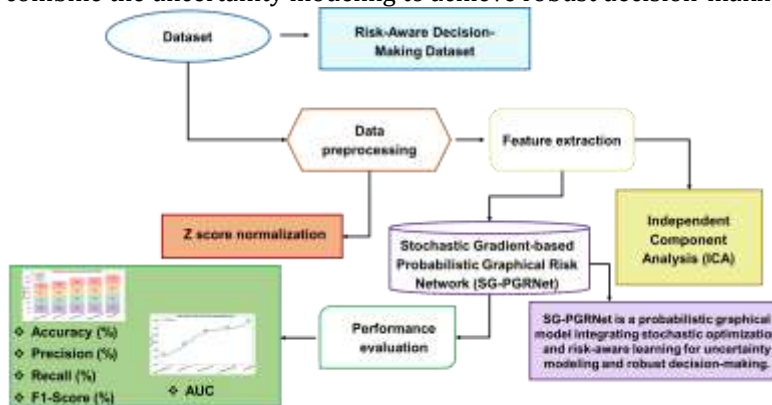


Figure 1: Risk-Aware Decision-Making Pipeline for SG-PGRNet method

3.1 Data collection

The 4000 observations dataset with 17 attributes, all of which are structured and unstructured numeric attributes, intended to assist in decision-making in uncertain circumstances. Measurements of returns, risk, CVaR, uncertainty, dynamism, and dependency are all measured in different situations of choice. In each of the observations, factors such as variability, probability measures, and risk at the system level dataset is split into 80% training and 20% testing in various disciplines. The fact that it categorizes risk levels in the target attribute as either low, medium, or high is what makes it possible to effectively assess the ML algorithms based on risks and uncertainties.

Kaggle Source:

<https://www.kaggle.com/datasets/zara2099/risk-aware-decision-making-dataset/data>

Data feature exploration: Figure 2(a) presents a correlation between various financial parameters, their dependence on each other, and their influence on the general state of the market, exposing dependencies that create uncertainty and risk. Figure 2(b) decomposition of financial risk through time into three components – trend, seasonality, and residuals, thus showing the variation of risk depending on economic, psychological, and exogenous factor.

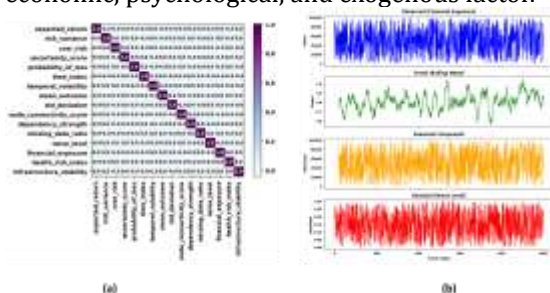


Figure 2: Risk Feature Relationships and Temporal Dynamics Analysis (a) Risk Feature Correlation Matrix, (b) Temporal Decomposition of Financial Exposure

Figure 3 depicts the behavior of the stability index over time as well as the volatility changes of the initial sequence and the smoothed-out sequences, which can be seen through the use of moving averages.

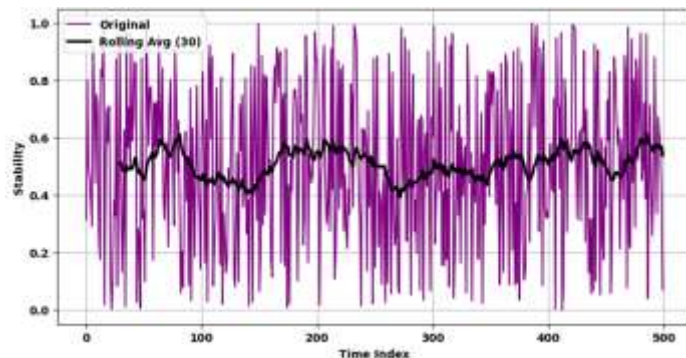


Figure 3: Temporal Stability and Volatility Measurement

3.2 Data preprocessing using z-score normalization

The experiment enhanced the application of probabilistic ML to risk-aware decision-making through Z-score normalization of data inputs to minimize noise and achieve consistency. By converting the various numerical characteristics and time-related characteristics to zero means and unit standard deviations, the research aims to normalize these aspects and also to ensure that there is consistency in terms of their scaling. This normalization is vital in situations where there is uncertainty, as it can be used to enhance learning, consistency, and model stability in such cases. Equation (1) describes how the statistics of the training data can be exploited to normalize both the training and testing data at all times.

$$Y - \text{Scored } EMG_{s,c,t} = (EMG_{s,c,t} - \mu_{train,t}) / \sigma_{train,t} \quad (1)$$

In Equation (1), Y represents the normalized data representation, $scored$ represents the normalized output following transformation, s encodes the variance among entities in the dataset, c is the process of normalization that is learned using only the training set to make probabilistic inferences, and t captures the uncertainty characteristics that are of interest when making decisions that are risk sensitive. EMG is the first of the feature data before it is normalized, train refers to the training dataset which is used to calculate the statistical values of normalization, and μ is the average value of the training dataset and σ mentions to the standard deviation of the training data.

3.3 Feature extraction using Independent Component Analysis (ICA)

A technique to break down multi-dimensional data into independent variables (in the statistical sense) is called Independent Component Analysis (ICA). This is known as blind source separation, and this technique is directly connected to it. With such a method, redundancy in the data is eliminated, and independent factors are identified. ICA is utilized in the current work to increase the feature representation. This method enhances the quality of the representation by going beyond second-order decorrelation, therefore, supporting risk-sensitive decision-making.

$$w = Bt \quad (2)$$

In Equation (2), w separates the independent components from the input signal, B represents the mixing matrix. It indicates how the original sources have been mixed to produce the output signal and t indicates the time index.

$$v = Xw = XBt \quad (3)$$

X is the observed input data that has a combination of signals, w represents the weight matrix, used to extract the combined signals independently and v is the output, where v is the set of independent components from X through the weight matrix w are represented in Equation (3).

$$e_v(v) = \prod_j e_{v_j}(v_j) \quad (4)$$

In Equation (4) e denotes the distribution of a random variable or component, v denotes a vector that contains several variables (v_1, v_2, v_3, \dots) and $e_v(v)$ is the joint function of all components of v . \prod denotes the product of several factors, similar to how Σ denotes summation of several factors and e_{v_j} is the function (or probability density function) of the individual component of v_j and j is an index (like 1, 2, 3, ...), \prod_j means multiplication for all values of indices of j and finally $e_{v_j}(v_j)$ is the value of the function (probability density) corresponding to the j -th independent component of v_j .

3.4 Risk-Sensitive Decision-Making in financial using SG-PGRNet

The proposed SG-PGRNet is a risk-sensitive decision-making that incorporates the combination of stochastic gradient optimization and probabilistic graphical modeling. This method includes the application of SG optimization in the variational inference, PGRNet models of dependency models. It also has a risk-sensitive objective function that allows the incorporation of sensitivity to both extremes and averages through the optimization of variance, expected loss, and CVaR. It is through achieve by integrating uncertainty, identifying complex relationships, and adapting to new data distribution situations, hence ensuring accuracy and risk reasonableness.

PGRNet for Decision-Making: In the use of Probabilistic Graphical Models (PGMs), it is possible to represent complex multivariate probability distribution by decomposing it to simpler local functions that are defined based on a set of random variables. In this research, PGMs are utilized in modeling the interactions of latent and observed variables in financial systems under uncertain environments, to improve decisions and financial predictions based on risk sensitivity. The Markov Network makes use of an undirected graph, with its local function as a potential function, while the Bayesian Network uses a directed graph with conditional probabilities.

$$O(W_1, \dots, W_m) = \prod O(W_i|V_j) \quad (5)$$

In Equation (5), O is the overall function of the system that combines the effects of all the variables in the model, m represents the total number of variables or components in the system and W_1, \dots, W_m is the set of all variables in the system ranging from 1 to m . \prod represents the combined product of multiple values across an index. i is simply an identifier for indexing the variables in the model and j is simply a label for positioning variables within the model or equation, W_i represents the single element or characteristic that is located at position i within a set of variables and V_j is the j -th element or characteristic within the set of variables V . $W_i|V_j$ represents the conditional relationship of variable W_i based on V_j .

$$O(W_1, \dots, W_m) + \frac{1}{Y} \prod \pi_i[D_i] \quad (6)$$

In this Equation (6), Y is a normalization constant that helps normalize the contribution of the second term to the model, π_i denotes the i -th weight, function, or probability factor used in the modeling process and D_i is an indicator for the i -th data element/decision variable in a dataset/model.

SGD for Parameter Optimization: The current research uses the Stochastic Gradient Descent (SGD) optimization method to iteratively minimize the objective function for probabilistic predictions under uncertainty in financial markets. Model parameters are initialized and updated gradually in the negative direction of the gradient of the loss function. The learning rate controls the step size toward the optimum. Objective Function

Incorporating prediction error and penalties to ensure generalization, minimize over-fitting, and allow for robust and risk-sensitive decision-making in complex financial situations.

$$\theta_i = \theta_i - \alpha \frac{\partial z}{\partial w} I(\theta) \quad (7)$$

In Equation (7), i is merely an identifier for the different model parameters, θ encompasses the entire set of tunable parameters learned by the model during training, θ_i is the adjustable i -th weight that changes to optimize the model and α is the step size that determines how fast the parameters change during training, ∂z is a small change in the function z for optimizing purposes, ∂w is a small change in a model parameter needed for updating the learning process and $\frac{\partial z}{\partial w}$ is the gradient that indicates the effect of the weight w on the model output/loss z . I can be either an indicator function or regularization term based on usage and $I(\theta)$ is an indicator/control function that controls how parameters are updated when learning.

$$I(\theta) = \frac{1}{m} \sum_{j=1}^m K(z_j, e(w)) + \alpha Q(X) \quad (8)$$

In Equation (8), m refers to the dataset size or the number of observations utilized during training, \sum refers to summation notation, which denotes adding many terms together within an index. j refers to the index or subscript number utilized in distinguishing elements within a dataset or summation, K refers to a function, which measures the discrepancy or similarity between two variables within the model. z_j refers to the actual value for the j -th data point utilized in assessing the accuracy of the model. e is model output (prediction function); w refers weight or parameter set of the model. It is the one that dictates how the input is transformed into output. This is the one that gets adjusted during the learning process. $e(w)$ represents how the model maps weights w into a prediction or estimated result and Q quality function of the input data X .

Algorithm 1: SG-PGRNet for Risk-Sensitive Decision-Making

1 Load Dataset

- 2 Preprocess Data
 - 3 Normalize the features using Z-score normalization:
 - 4 $x' = \frac{x-\mu}{\sigma}$
 - 5 Feature Extraction
 - 6 Apply Independent Component Analysis (ICA) to extract independent latent features:
 - 7 $X = AS, S = WX$
 - 8 where X is observed data, S are independent components, A is the mixing matrix, and W is the unmixing matrix.
 - 9 Initialize SG-PGRNet Model
 - 10 Construct Probabilistic Graphical Model (PGM)
 - 11 Initialize parameters θ
 - 12 Define variational distribution $q(\theta)$
 - 13 Initialize Training Parameters
 - 14 Learning rate η
 - 15 Risk coefficients λ_1, λ_2
 - 16 Initial loss L_{old}
 - 17 Evaluate Initial Loss
 - 18 $L_{old} = SG-PGRNet(\theta)$
 - 19 For Iteration $iter = 1$ to $iter_{max}$
 - a. Update Model Parameters:
 - 20 $\theta_{new} = \theta_{old} - \eta \nabla_{\theta} L$
 - 21 b. Perform Variational Inference:
 - 22 $q(\theta) \approx p(\theta | D)$
 - 23 c. Compute New Loss using Risk-Sensitive Function:
 - 24 $L_{new} = \mathbb{E}[Loss] + \lambda_1 Var(Loss) + \lambda_2 CVaR_{\alpha}(Loss)$
 - 25 d. Update Rule:
 - 26 If $L_{new} < L_{old}$:
 - 27 $\theta_{old} = \theta_{new}, L_{old} = L_{new}$
 - 28 Else retain previous parameters.
 - 29 End For
 - 30 Train Final Model
 - 31 Train SG-PGRNet using optimized parameters θ_{final}
 - 32 For Each Data Instance $x \in W$
 - a. Predict Probabilistic Output:
 - 33 $y_j \sim p(y | x_j, \theta)$
 - 34 b. Risk-Sensitive Decision:
 - 35 $d_j = arg \min (\mathbb{E}[Loss] + \lambda_2 CVaR_{\alpha})$
 - 36 c. Execute Decision and Observe Outcome
 - 37 **Return**
 - 38 Optimized risk-sensitive decision strategy with uncertainty estimation.
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Algorithm 1 present SG-PGRNet integrates probabilistic graphical modeling with risk-sensitive optimization, allowing for robust decision-making in uncertain conditions. The model pre-processes data and derives latent representations through ICA, fine-tunes its parameters using SGD with CVaR objective function, and produces probabilistic. The proposed SG-PGRNet framework integrates probabilistic graphical models with risk-sensitive optimization to enable robust decision-making in financial systems under uncertainty. Financial datasets are preprocessed, normalized, and latent features are extracted via ICA. The model is trained using an SGD approach with variational inference along with a risk-sensitive loss function that uses CVaR. The resultant model produces probabilistic predictions, making it possible for the model to make optimal risk-aware decisions.

4. RESULT AND DISCUSSION

The proposed SG-PGRNet architecture has undergone evaluation and shown increased predictive accuracy, uncertainty modeling capability, and decreased risk cases. The algorithm is programmed using Python and performed under the Windows operating system with an Intel® Core™ i7 CPU.

Accuracy (%) - This refers to the effectiveness of the model in terms of making correct predictions based on its performance. Nevertheless, it might be unreliable in capturing rare high-risk instances in uncertain settings. Precision (%) - This measure represents the proportion of actual high-risk cases captured in the

model's predictions. It ensures that there are fewer chances of predicting an instance incorrectly and thus ensures more efficient risk-based decision-making. Recall (%) - This measure captures how well the model predicts instances of actual high-risk events. Recall ensures that risky instances are not ignored, which would be crucial for decision-making in uncertain environments. F1-Score (%) - This measure combines both recall and precision in a balanced manner. F1-Score can be quite effective in assessing a model's performance in uncertain environments where precision and recall need consideration. AUC (Area Under the Curve) - This measure assesses the discriminative capacity of a model in terms of capturing differences in low and high-risk instances in its prediction process.

PERFORMANCE EVALUATION USING EXISTING DATASET [16]: SG-PGRNet trained to identify patterns associated with risks and uncertainties was done using the existing database [16], which contained structured quantitative and temporal data. This proposed methodology works better compared to the base models such as (Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting [16]). It reduces the risky conditions, improves the identification of uncertainty, and increases the accuracy of the prediction. This can be supported by the increased performance indices as shown in Table 2.

Table 2: Comparative performance demonstrating better outcome in existing data

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression [16]	78.6	71.4	65.2	68.2	0.74
Decision Tree [16]	83.2	76.8	72.5	74.6	0.81
Random Forest [16]	89.3	84.7	80.9	82.8	0.91
Gradient Boosting [16]	90.1	85.9	82.4	84.1	0.93
SG-PGRNet [proposed]	93.4	90.6	89.2	89.9	0.96

PERFORMANCE EVALUATION USING THE PROPOSED DATASET: The existing models such as (Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting [16]) were trained using Risk-Aware Decision-Making dataset, which contained both structured numeric and temporal features. Table 3 and Figure 4(a, b) shows the effectiveness of SG-PGRNet compared to the existing models achieved better in accuracy (95.2%), precision (93.5%), recall (94.3%), F1-score (94.9%), and AUC (0.98). The research shows that there is more precise risk-sensitive decision-making uncertainty evaluation and high detection of high-risk cases compared to traditional methods.

Table 3: Comparative performance demonstrating better outcome in proposed data

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	80.2	73.6	68.1	70.7	0.76
Decision Tree	85.1	78.9	74.3	76.5	0.83
Random Forest	90.5	86.2	82.7	84.4	0.92
Gradient Boosting	91.6	87.8	84.9	86.3	0.94
SG-PGRNet [proposed]	95.2	93.5	94.3	94.9	0.98

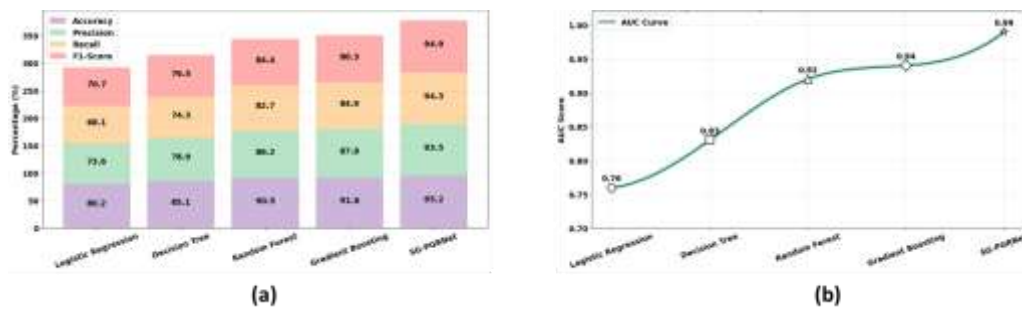


Figure 4: Graphical representation of (a) Classification Model Performances Using Various Metrics (b) Comparison of AUC Scores for ML Models

Classic frameworks [16] usually do not consider uncertainty and risks, and hence produce unreliable and less optimal results in the presence of complicated financial scenarios or dynamic processes. The introduced SG-PGRNet framework is capable of overcoming the mentioned weaknesses, as it considers probabilistic models and CVaR optimization for better decision-making under uncertain conditions.

5. Conclusion

The combination of probabilistic graphical modeling with risk-sensitive optimization allows SG-PGRNet to effectively deal with uncertainties in decision-making. Compared with conventional methods, the research can provide a better representation of variabilities and risk patterns because of the modeling of structured dependence among the variables and the modeling of uncertainty-aware learning. Due to the structured dependencies and uncertainty-aware patterns, it can produce outstanding results in accuracy, precision, recall, F1 score, and AUC, which are 95.2%, 93.5%, 94.3%, 94.9%, and 0.98, respectively. High recall means that the model has the capability to detect high-risk cases, which is significant in risk-sensitive situations. In general, SG-PGRNet is capable of providing robust predictive accuracy, high-quality uncertainty quantification, and improved risk discrimination. However, there are several limitations of the proposed SG-PGRNet despite its high accuracy. Future directions include enhancing scalability, expanding deployment, and integrating deep probabilistic and hybrid learning methods.

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