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Deep Bayesian Modeling for Maritime Situational Awareness with Multisource and Heterogeneous Information

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Abstract: Maritime situational awareness is a core research field in marine science, whose intrinsic complexity stems from the inherent nature of the ocean as an open, complex giant system and the technical challenges of cross-domain multi-platform coordination and multi-source heterogeneous data processing. To address this challenge, this paper proposes an intelligent prediction framework based on multi-source data fusion via a deep Bayesian network. The model integrates deep learning architectures with probabilistic graphical modeling, effectively leveraging the powerful representational capacity of neural networks together with the strengths of Bayesian inference in uncertainty modeling and causal reasoning. A central contribution of this framework is its multimodal fusion mechanism, which captures the complex, nonlinear, and non-stationary evolution of maritime situations. By moving beyond the limitations of conventional methods, our approach extracts latent situational elements from multimodal inputs and performs probabilistic density estimation of future states through variational inference. Experimental results demonstrate that the predictions generated by our model align closely with actual situational developments, with all key evaluation metrics showing significant improvements over existing forecasting techniques.

1. Introduction

Owing to the dynamic and multidimensional nature of modern maritime environments [1], situational awareness and forecasting are now indispensable for robust command, control, and decision-making systems [2].The contemporary maritime domain is characterized by multi-domain integration, highly dynamic nonlinear evolution, and diverse operational activities across aerial, surface, and subsea dimensions. This environment constitutes a complex system featuring tight spatiotemporal coupling and deeply interwoven information flows [3]. The domain inherently involves multi-source, heterogeneous data streams related to underwater maritime noise. These data are captured by a variety of platforms, notably autonomous underwater vehicles and vessel-borne sensors, providing a complex acoustic profile of the maritime environment. These data sources exhibit significant heterogeneity in spatial and temporal resolution, data formats, measurement precision, and operational characteristics, presenting substantial challenges for integrated situational analysis. This multifaceted nature of maritime data necessitates sophisticated fusion methodologies capable of reconciling structural and semantic differences while preserving the unique informational value of each data modality. Within this context, situational awareness necessitates not only comprehensive and accurate acquisition and interpretation of multi-source environmental elements but also the capability to conduct real-time forecasting and risk assessment of future situational trends. These functionalities are essential to enabling proactive maritime domain management and maintaining decision-making superiority [4].

However, the advancement of predictive models in this field has long been constrained by a fundamental trade-off: the pursuit of high prediction accuracy versus the equally critical need for reliable uncertainty quantification. [5]. Conventional approaches to maritime situational prediction have largely followed by manually constructed architectures and prior probabilities, limiting their ability to capture complex spatiotemporal patterns from high-dimensional, multi-source environmental data. Deep learning techniques, excel at automatic feature extraction from large-scale datasets and deliver strong performance in deterministic prediction tasks. Yet, they inherently lack mechanisms for uncertainty quantification and interpretable reasoning. In the highly volatile maritime domain, situation evolution exhibits strong non-stationarity, multimodal distribution characteristics, and complex temporal dependencies [6]. These challenges place greater demands on situational awareness systems, which must not only rapidly extract critical situational elements from multi-source heterogeneous data within complex sensor networks but also construct adaptive operational models that update dynamically based on historical and real-time observations. Moreover, they must predict future situation trends across multiple time scales to facilitate rapid response and optimal decision-making in the face of sudden tactical events. To address these complex and pressing challenges, this study introduces a novel framework based on Bayesian deep learning for integrating multisource and heterogeneous information, designed to enhance situational awareness, analysis, and prediction capabilities in complex environments, thereby providing enhanced support for operational decision-making in complex maritime environments, as shown in Figure 1.

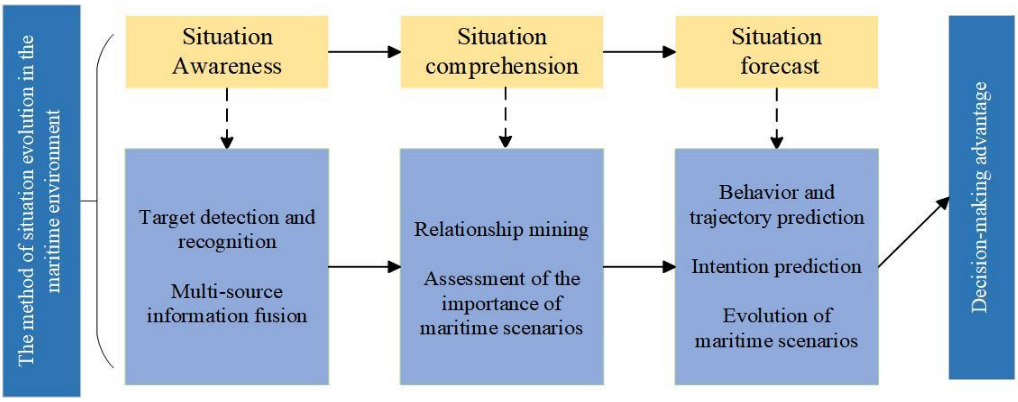

Figure 1: Maritime Situation Evolution Diagram

2. Maritime Situation Awareness

Maritime Situational Awareness and Prediction represent a foundational technology for modern maritime safety and operational management [7]. This capability encompasses the comprehensive, real-time acquisition and accurate interpretation of diverse elements within complex maritime environments through integrated technical approaches, coupled with scientifically-grounded forecasting of future developmental trends. The analytical framework requires precise monitoring of static and dynamic parameters, including vessel distribution patterns, equipment status, and movement trajectories.

Situational Awareness and Prediction is a systematic, hierarchical model for analyzing the evolution of maritime situations. It adheres to the "Data-Information-Knowledge-Decision" cognitive paradigm, aiming to achieve an in-depth understanding and proactive forecasting of the overall maritime situation. This process spans from low-level, multisource data perception to high-level situational evolution and decision support. The core of this framework lies in integrating static environmental elements with dynamic entity behaviors to ultimately provide decision-makers with a decisive advantage.

Against the backdrop of increasing complexity and uncertainty in modern maritime operations, traditional maritime situational awareness and prediction methods face multiple challenges. These include difficulties in multi-source data fusion, insufficient adaptability to dynamic environments, and limitations in capturing nonlinear relationships. In this context, Bayesian networks have emerged as a fundamental methodology due to their capability to manage probabilistic reasoning and reveal causal dependencies. Static Bayesian networks typically achieve parameter construction and probabilistic inference through expert knowledge-driven parameterization and algorithmic optimization. For instance, Danyi Li et al. generated network parameters using expert experience and constructed Bayesian networks via belief propagation algorithms [8]. Similarly, Xun Zhang et al. employed Bayesian networks to establish assessment models for situational risk evaluation through probabilistic inference [9]. Kong D. et al. further enhanced model performance by integrating multiscale scenario analysis theory to examine correlations among maritime safety factors [10].These approaches demonstrate the potential of Bayesian methods in addressing uncertainty in maritime environments. However, they primarily operate within static frameworks, which may limit their effectiveness in dynamically evolving scenarios characterized by heterogeneous data sources and rapidly changing conditions.

However, static models demonstrate significant limitations in handling high-dimensional dynamic scenarios, primarily due to their reliance on manual, expert-driven structural construction, which tends to be inefficient and susceptible to overlooking critical dependencies. To overcome these constraints, dynamic Bayesian networks extend the conventional framework by incorporating temporal dimensions. For instance, Qin Zhang et al. developed a dynamic Bayesian-based assessment method for real-time situational prediction [11], while Hanwen Fan et al. utilized a dynamic Bayesian model to probabilistically capture interactions among influencing factors within a causal inference framework, effectively mitigating data imbalance [12]. Xiao Chen et al. proposed a hybrid dynamic–static model for comprehensive maritime target risk evaluation [13]. Zhen-Hua Fan et al. leveraged Markov properties to design a fast approximate inference algorithm, substantially improving computational efficiency [14]. Sun H. et al. further integrated dynamic Bayesian networks with utility theory to optimize risk assessment, aligning with the growing adoption of deep learning and hybrid methodologies [15].Subsequently, researchers began exploring data-driven approaches. Zhai Yongcui et al. introduced a deep learning-based framework for maritime big data situational awareness [16], and Xiang Fan et al. applied Long Short-Term Memory (LSTM) networks to temporal navigation state prediction, enabling proactive awareness [17]. Wei Li et al. proposed a unified multi-source data representation model based on knowledge graphs to achieve semantic association for situational inference [18]. Xiuli Du et al. improved the D-S evidence theory combination rules to resolve conflicts in multi-source information fusion [19]. Traditional dynamic Bayesian networks with deep learning, continue to face fundamental challenges in balancing model complexity with real-time computational requirements [20]. High-dimensional state spaces often lead to inference inefficiencies, while limited adaptability to unknown behavioral patterns and deceptive scenarios remains an issue. Heavy reliance on historical data also constrains their effectiveness in rapidly evolving or novel situations. Furthermore, multi-source heterogeneous data fusion continues to be impeded by semantic inconsistencies and quality variability, with core difficulties persisting in the dynamic evaluation of evidence reliability.

This paper proposes a Bayesian Deep Network framework that tackles maritime situation prediction by marrying the capabilities of traditional Bayesian deep networks with the modeling of multi-source, heterogeneous data.

Specifically, deep learning excels in automatically learning high-order semantic features from large-scale, multimodal maritime perception data without relying on handcrafted feature engineering, thereby significantly improving the efficiency and accuracy of feature extraction. Meanwhile, Bayesian inference, grounded in probability theory, focuses on modeling and quantifying uncertainty [21]. Through prior knowledge integration and posterior updating mechanisms, it dynamically refines estimates of unknown states as new observations become available, enabling interpretable reasoning and trustworthy decision-making. By seamlessly integrating the representational power of deep neural networks with Bayesian uncertainty quantification [22], our framework enables dynamic and adaptive fusion of multi-domain heterogeneous data in maritime environments, establishing a unified probabilistic modeling architecture for situational prediction. The main contributions of this paper are summarized as follows:

1) We propose a maritime situational prediction model based on Bayesian deep networks that effectively overcomes limitations of existing approaches.

2) We establish an experimental validation framework simulating five distinct submarine behavioral patterns and systematically demonstrate the model's superior capability in delivering risk-aware and reliable predictive outcomes. Employing uncertainty-calibrated confidence intervals as the core evaluation metric alongside conventional accuracy measures, our approach provides a more robust theoretical foundation for supporting critical decision-making processes in maritime operations.

3. Multisource Deep Bayesian Learning Model

Bayesian inference [23] fundamentally treats all unknown parameters in a model as random variables. Through systematic application of Bayes' theorem, it combines prior knowledge with observed data to derive the posterior probability distribution of these parameters. This process follows the formula:

$$p\left(w|D\right)=\frac{p\left(D|w\right)p\left(w\right)}{p\left(D\right)} \tag{1}$$

The prior distribution $p(w)$ mathematically encodes domain knowledge or historical experience about the parameters before observing data D. The likelihood function, $p(D/w)$ describes the probability of observing the available data D under specific parameter values w. The marginal likelihood $P(D)$, obtained by integrating over the parameter space, synthesizes prior beliefs and observed evidence. Thus, the posterior distribution $p(w/D)$ represents the updated probabilistic assessment of the parameters after incorporating the information from the data D.

The Bayesian paradigm offers a coherent framework for uncertainty quantification, a feature rooted in its fundamental treatment of parameters as random variables. This framework primarily manifests in two forms: parameter uncertainty and predictive uncertainty. The posterior distribution $p(w|D)$ fully characterizes uncertainty by describing the probability density over all plausible parameter values. The ultimate objective of Bayesian learning is typically predictive inference. For a new inputx^*, its predictive distribution is obtained through Bayesian model averaging:

$$P(y^* \mid x^*, D) = \int P(y^* \mid x^*, w) P(w \mid D) dw \tag{2}$$

Predictions thereby incorporate both aleatoric uncertainty arising from data randomness and epistemic uncertainty stemming from imperfectly known model parameters. By sampling from the predictive distribution, the complete probability profile of future observations can be obtained, enabling direct quantification of prediction confidence intervals.

In maritime situational prediction scenarios, typically characterized by data scarcity, significant noise contamination, and high-stakes operational complexity, epistemic uncertainty emerges as a critical consideration. Modern maritime monitoring systems generate an abundance of multi-sensor data streams. The fundamental challenge thus shifts from data acquisition to the coherent fusion of these diverse and often contradictory information sources.

The Bayesian inference framework addresses this challenge by systematically quantifying uncertainty throughout the entire modeling process, from parameter estimation to final predictive outputs. Through its inherent mechanisms of posterior distributions and Bayesian model averaging, the framework naturally incorporates uncertainty assessment without requiring external adjustments. More significantly, it establishes a unified probabilistic foundation for integrating heterogeneous data sources, enabling the modeling of distinct noise characteristics and reliability metrics for each sensor modality within a single coherent posterior representation. This integrated approach transforms situational awareness from basic perception to informed cognitive understanding by explicitly representing and propagating uncertainties across all data sources and processing stages.

In the deep Bayesian model developed in this study, the integration of Bayesian inference mechanisms within the neural network architecture overcomes the limitation in traditional models that treat parameters as fixed constants. Instead, all model parameters are defined as random variables following specific probability distributions. Within the framework of Bayesian neural networks, a probabilistic model is first constructed, where the network weights$W$ are treated as probability distributions. Given a prior distribution and a likelihood function, the objective shifts to solving for the posterior distribution.

Exact computation of the posterior distribution is typically intractable in complex deep Bayesian models. To address this challenge, our work employs variational inference to obtain a computationally feasible approximation of the posterior. In the Bayesian linear layer configuration, the prior distributions for both weights and biases are specified as Gaussian distributions with mean 0 and variance σ_0^2:

$$p(\mathbf{w}) = \mathcal{N}(\mathbf{w}|0, \sigma_0^2\mathbf{I}), \quad p(\mathbf{b}) = \mathcal{N}(\mathbf{b}|0, \sigma_0^2\mathbf{I}) \tag{3}$$

The variational posterior is modeled as a parameterized Gaussian distribution, with its mean and variance serving as learnable parameters. Specifically, for the weight matrix W, we assume:

$$q(\mathbf{W}|\ \boldsymbol{\theta}) = \mathcal{N}(\mathbf{W}|\ \boldsymbol{\mu}_w, \boldsymbol{\Sigma}_w) \tag{4}$$

where μ_w is the mean vector and Σ_w is the diagonal covariance matrix. Formally, the variational posterior $q_\theta(W)$ is defined as a Gaussian distribution with diagonal covariance structure:

$$q_\theta(\mathbf{W}) = \mathcal{N}(\mathbf{W} \mid \boldsymbol{\mu}_\theta, \boldsymbol{\Sigma}_\theta) \tag{5}$$

The variance is parameterized using its logarithmic value, as this formulation offers greater numerical stability during optimization and allows for an unbounded range of real values. Specifically, the parameterization is defined as:

$$\mathbf{\Sigma}_w = \mathrm{diag}(\exp(\psi_w)) \tag{6}$$

$$\mathbf{\Sigma}_b = \mathrm{diag}(\exp(\psi_b)) \tag{7}$$

$$\mathbf{\Sigma}_\theta = \mathrm{diag}(\exp(\boldsymbol{\psi}_\theta)) \tag{8}$$

Where ψ_w and ψ_b denote the log-variance parameters of the weights and biases, respectively, defining the diagonal covariance matrix Σ_θ.During training, the reparameterization technique is employed to enable gradient-based optimization while maintaining stochasticity. Specifically, sampling from the variational posterior is performed as:

$$\mathbf{W} = \boldsymbol{\mu}_w + \epsilon_w \odot \exp(0.5 \cdot \boldsymbol{\psi}_w), \quad \epsilon_w \sim \mathcal{N}(0, \mathbf{I}) \tag{9}$$

$$b = \boldsymbol{\mu}_b + \epsilon_b \odot \exp(0.5 \cdot \boldsymbol{\psi}_b), \quad \epsilon_b \sim \mathcal{N}(0, \mathbf{I}) \tag{10}$$

Where $\odot$ represents the element-wise product. This reparameterization approach enables gradient backpropagation by first sampling ϵ from a standard normal distribution and then applying a deterministic transformation to obtain the required samples. In variational inference, the objective is to minimize the Kullback-Leibler divergence between the variational posterior and the true posterior, which is equivalent to maximizing the evidence lower bound. When both the prior distribution and variational posterior are diagonal Gaussian distributions, the KL divergence admits a closed-form expression. For a single weight component w_i, the KL divergence is given by:

$$KL\left(q\left(w_i\right) \| p\left(w_i\right)\right) = \frac{1}{2}\left(\frac{\mu_i^2 + \sigma_i^2}{\sigma_0^2} - 1 - \log\frac{\sigma_i^2}{\sigma_0^2}\right) \tag{11}$$

Where μ_i^2 and σ_i^2 denote the posterior mean and variance of this component, respectively. Thus, the total KL divergence for the fully connected layer with parameters is given by:

$$\mathrm{KL}_{\text{layer}} = \sum_i \mathrm{KL}(q(w_i) \| p(w_i)) + \sum_j \mathrm{KL}(q(b_j) \| p(b_j)) \tag{12}$$

The complete Bayesian network architecture comprises multiple Bayesian linear layers combined with ReLU nonlinear activation functions, with Dropout regularization inserted between successive layers. During forward propagation in the Bayesian deep network, input data flows sequentially through three Bayesian linear layers, where ReLU activation and Dropout are applied after each linear transformation. The loss function is constructed to minimize the variational lower bound, which consists of two key components: the negative log-likelihood and the KL divergence term. Specifically, the loss function is defined as:

$$\mathcal{L}(\theta) = \mathrm{E}_{q(\theta)}\left[-\log p\left(D|\theta\right)\right] - \beta \cdot KL\left(q\left(\theta\right) \| p\left(\theta\right)\right) \tag{13}$$

Where θ represents the model parameters, D denotes the training dataset, and serves as a trade-off coefficient. The KL weighting factor β balances the trade-off between model fit and complexity. During training, stochastic gradient descent is employed to optimize the parameter set $\theta = \{\mu_\theta, \psi_\theta\}$:

$$\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L}(\theta) \tag{14}$$

To mitigate the risk of gradient explosion during training, gradient clipping is applied to constrain the norm of the gradients, thereby enhancing numerical stability and promoting stable convergence:

$$\text{if } \|\mathbf{g}\| > \lambda: \quad \mathbf{g} \leftarrow \lambda \frac{\mathbf{g}}{\|\mathbf{g}\|} \tag{15}$$

The model outputs a probability distribution over possible categories, which is approximated through Monte Carlo sampling:

$$p(y \mid \mathbf{x}, \mathcal{D}) \approx \frac{1}{T} \sum_{t=1}^{T} \text{Softmax}(f_{\mathbf{W}_t}(\mathbf{x})) \tag{16}$$

Where $W_t \sim q_\theta(W)$ represents the Monte Carlo sample drawn from the variational posterior. The training objective is to minimize a weighted combination of the cross-entropy loss and the KL divergence term, formulated as:

$$\text{Loss=CrossEntropy}\left(y, y^*\right) + \beta \cdot KL \tag{17}$$

Here, the first term corresponds to the cross-entropy between predicted and true labels, while the second term acts as a Bayesian regularizer, withβ controlling the trade-off between data fidelity and model complexity. The KL divergence serves as a Bayesian regularization term, quantifying the dissimilarity between the learned parameter distribution and the prior distribution. The coefficient β controls the relative influence of this regularization term in the total loss function, with larger values imposing stronger Bayesian constraints on the model parameters. Compared to traditional neural networks employ deterministic weight parameters, Bayesian neural networks represent each weight as a probability distribution. This probabilistic formulation enhances the model's capacity to capture epistemic uncertainty and improves generalization performance in data-scarce scenarios. The corresponding network architecture is as follows:

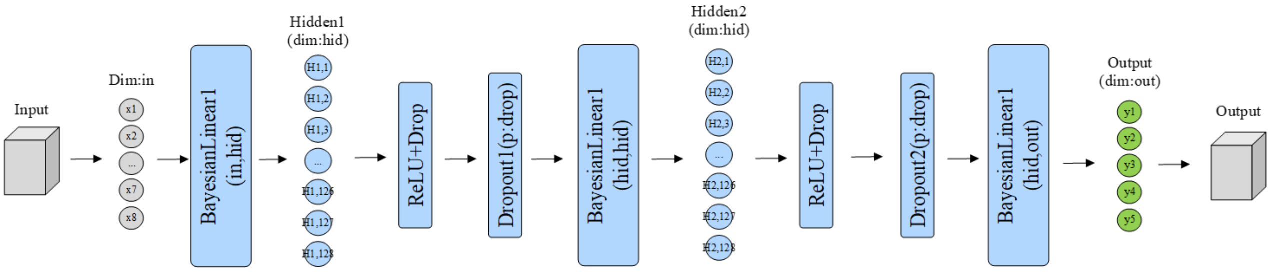

Figure 2: Deep Bayesian Network Architecture

As shown in Figure 2, the deep Bayesian network architecture is specifically engineered for multi-source heterogeneous information fusion, adopting a multi-tiered design. Within this hierarchical structure, disparate input data from diverse sources are initially transformed into a unified high-dimensional feature space. These transformed representations then undergo successive stages of linear transformation, nonlinear activation, and structured regularization through dropout mechanisms. The linear operations facilitate cross-modal feature integration and dimensional compression, while the nonlinear activations enable the learning of complex interdependencies across different data modalities. Through this layered architecture that systematically combines linear processing, nonlinear transformation, and regularization techniques, the final output layer generates precise task-specific predictions.

4. Experiments

This section systematically validates the proposed Multisource and Heterogeneous deep Bayesian model, focusing on its predictive performance in maritime environments. The experiments assess the model's accuracy under complex, dynamic, and multi-source conditions. Our multifaceted evaluation demonstrates the framework's practical utility and superior performance in real-world operational scenarios.

4.1 DATASETS

This study establishes a comprehensive multimodal dataset for maritime situational awareness research, systematically integrating simulated submarine behaviors, multi-sensor data generation, and trajectory estimation through advanced data fusion techniques. The dataset encompasses five representative operational modes of underwater vessels: active tracking, silent operation, routine navigation, underwater search, and tactical maneuvering. Each operational mode exhibits distinctive kinematic patterns and sensor signatures, providing a diverse foundation for model validation.

The core innovation of our dataset lies in its multimodal fusion architecture, which synchronizes and correlates data streams from heterogeneous sensing modalities including acoustic hydrophone arrays, magnetic anomaly detectors, surface surveillance radar, and electronic support measures. This integrated approach enables complementary information fusion across different physical domains, capturing electromagnetic emissions, acoustic signatures, and magnetic perturbations simultaneously. Each sensor modality contributes unique observational characteristics: acoustic arrays provide precise bearing estimation, magnetic detectors offer reliable proximity awareness.

To evaluate the fusion system's capabilities under various operational conditions, we simulate distinct behavioral scenarios incorporates critical environmental factors including oceanographic conditions, background noise profiles, and thermal layer structures to simulate real-world sensing challenges. Through this comprehensive multimodal approach, our dataset provides a solid foundation for developing and validating advanced situational awareness systems. The integration of multiple sensing dimensions within a unified probabilistic framework represents a significant advancement over conventional single-modality approaches, offering enhanced capabilities for accurate trajectory estimation and behavioral recognition across diverse operational scenarios and environmental conditions.

1	DOA 1	DOA 2	DOA 3	DOA 4	Position	Tracking	Label	track x	track y	track z
2	66.07157349	26.97927518	-0.55304137	41.1651007	[7.55590775, 1490.19667688, -28.13643193]	[6.55677945e+00, 8.24280846e-01, 1.49149298e+03, -1.06945343e+00, -2.83828542e+01, 2.03298335e-01]	3	6.556779453921857, nan, nan	1491.4929840714199, nan, nan	-28.38285415479201, nan, nan
3	65.99254979	27.1713031	-0.67936358	40.7741342	[7.89725555, 1473.99595526, -23.26034135]	[8.18933372e+00, 3.17790750e-01, 1.47527203e+03, -3.28228801e+00, -2.36915927e+01, 9.51127454e-01]	3	8.18933371648475, nan, nan	1475.2720328658652, nan, nan	-23.6915927382819, nan, nan
4	65.57796866	27.50205544	-0.28557065	40.5789241	[-17.41982544, 1444.19152457, -38.92977579]	[-14.26935261, -4.33854845, 1445.89070499, -5.7936445, -36.61380673, -2.47183096]	3	-14.269352607039835, nan, nan	1445.8907049942331, nan, nan	-36.61380673444972, nan, nan
5	65.92314884	28.00822498	-0.39500715	40.4630554	[10.22078145, 1452.27412498, -34.55938189]	[4.74702226e+00, 3.60877058e+00, 1.44808412e+03, 2.89796018e-01, -3.62677307e+01, 8.51078017e-03]	3	4.747022587926045, nan, nan	1448.0841222428364, nan, nan	-36.267730747836, nan, nan
6	65.86296319	28.5079796	-0.26643298	39.8603931	[15.53588088, 1428.4910167, -39.64773418]	[1.63947551e+01, 2.36036207e+00, 1.43098206e+03, -3.33103643e+00, -3.92425587e+01, -5.80428305e-01]	3	16.394755062156094, nan, nan	1430.9820599003554, nan, nan	-39.2425586550248, nan, nan
7	65.35979162	28.65368528	-0.62541168	39.7425173	[-17.2404861, 1398.48953042, -26.11978662]	[-11.85961497, -5.45770628, 1400.3650642, -6.05606941, -28.01753288, 2.17687802]	3	-11.859614970481669, nan, nan	1400.365064203684, nan, nan	-28.01753287774245, nan, nan
8	65.40876739	28.97650095	-0.52598686	39.5017816	[-9.45595816, 1391.06861365, -29.91452889]	[-1.29722921e+01, -3.48697188e-01, 1.38858357e+03, -2.44545920e+00, -2.84008775e+01, -2.23609642e-02]	3	-12.97229210396679, nan, nan	1388.5835698731357, nan, nan	-28.400877500588322, nan, nan
9	65.53636188	29.26085355	-0.59651728	38.8304918	[8.5194698, 1378.74565351, -27.12415297]	[5.76780833e+00, 3.64928904e+00, 1.37846269e+03, -2.03432922e+00, -2.72885912e+01, 2.16557134e-01]	3	5.767808325080889, nan, nan	1378.4626884241234, nan, nan	-27.28859118977711, nan, nan
10	65.32420555	29.61246634	-0.74167375	38.6448668	[-2.27244852, 1359.20919184, -21.84310508]	[8.40587103e-01, -8.73747473e-01, 1.36028472e+03, -3.59700305e+00, -2.23597633e+01, 9.67227696e-01]	3	0.8405871027341476, nan, nan	1360.2847213613002, nan, nan	-22.359763342990018, nan, nan
11	65.07789333	29.84736198	-0.91486845	37.8782687	[-9.75806811, 1328.06114016, -15.64642521]	[-9.02028230e+00, -1.94570189e+00, 1.32974736e+03, -6.04697012e+00, -1.58687349e+01, 1.29022914e+00]	3	-9.020282300419655, nan, nan	1329.7473601416268, nan, nan	-15.868734926792904, nan, nan
12	65.31308544	30.20838956	-0.63590396	37.7205654	[10.16901536, 1330.67020341, -25.92433306]	[6.74438787e+00, 3.03005728e+00, 1.32698031e+03, -6.85803544e-01, -2.39695013e+01, -1.55001326e+00]	3	6.744387868903715, nan, nan	1326.9803145248818, nan, nan	-23.96950126773907, nan, nan
13	65.09574718	30.82387015	-0.34046347	37.8050049	[-2.02323506, 1312.28433779, -37.26651148]	[8.09273281e-01, -1.08539159e+00, 1.31361864e+03, -2.62445935e+00, -3.66096077e+01, -2.50445137e+00]	3	0.8092732806743861, nan, nan	1313.618641505428, nan, nan	-36.60960771191304, nan, nan
14	64.89607217	31.02620704	-0.33869231	37.7260751	[-13.60223679, 1297.92044233, -37.4654772]	[-1.25382300e+01, -2.63132374e+00, 1.29822550e+03, -3.06768349e+00, -3.88470837e+01, -4.97067694e-01]	3	-12.538229960462902, nan, nan	1298.2254968017803, nan, nan	-38.84708371609357, nan, nan
15	64.84080973	31.26731913	-0.53535216	37.2417311	[-10.87464566, 1281.85582126, -30.19542287]	[-1.26297467e+01, -8.12769562e-02, 1.28197795e+03, -3.24512751e+00, -3.15143360e+01, 1.41922652e+00]	3	-12.629746738719867, nan, nan	1281.9779492949383, nan, nan	-31.514335953348976, nan, nan
16	65.1895348	31.24171964	-0.47034968	36.8198661	[17.0758442, 1290.7144038, -32.34361482]	[1.35097958e+01, 5.09995753e+00, 1.28775824e+03, 1.04998927e+00, -3.14050380e+01, 5.55360223e-02]	3	13.50979579947463, nan, nan	1287.7582368139942, nan, nan	-31.405038048470832, nan, nan
17	64.53920315	32.01698195	-0.48101041	36.4234842	[-18.31101616, 1239.67284378, -32.46490444]	[3.90095834e+01, 5.09995753e+00, 1.29300818e+03, 1.04998927e+00, -3.11273579e+01, 5.55360223e-02]	3	39.00958342576508, nan, nan	1293.0081831444666, nan, nan	-31.12735793710302, nan, nan
18	64.82766054	32.23830371	-0.30038555	36.5140757	[2.13256526, 1251.12829734, -38.9750828]	[3.96366245e+00, -2.19477343e+00, 1.25251181e+03, -4.46166593e+00, -3.87365581e+01, -8.94699285e-01]	3	3.9636624460640064, nan, nan	1252.5118132516047, nan, nan	-38.73655814211016, nan, nan
19	64.93553572	32.52595558	-0.63892086	35.8248341	[18.17844591, 1238.44623606, -26.38628249]	[15.3273364, 2.27679727, 1237.5132369, -2.99838586, -28.29056935, 2.09191113]	3	15.327336402756988, nan, nan	1237.5132369017072, nan, nan	-28.290569353519977, nan, nan
20	64.654053	32.77605108	-0.76454067	36.1147466	[-1.69784593, 1226.1048033, -22.07401504]	[1.58793115, -2.60861278, 1225.69033964, -2.38214657, -21.58327359, 1.36225932]	3	1.5879311466068025, nan, nan	1225.6903396366533, nan, nan	-21.583273594731537, nan, nan
21	64.85104757	33.09214629	-0.45492873	35.3847994	[20.72930221, 1216.55390138, -33.28859889]	[16.91865993, 2.92768929, 1216.22542445, -1.90491797, -31.09622788, -1.82293291]	3	16.918659929162626, nan, nan	1216.22542445115, nan, nan	-31.096227883756935, nan, nan
22	64.70279662	33.45405968	-0.08867197	35.0528232	[16.38147679, 1197.32110413, -46.80362934]	[1.81783038e+01, 3.16323405e-01, 1.19843168e+03, -3.51894710e+00, -4.60230352e+01, -2.95738655e+00]	3	18.178303827487188, nan, nan	1198.431684303997, nan, nan	-46.023035169229054, nan, nan
23	64.3107758	33.33110752	-0.26185238	34.8684397	[-9.52925017, 1178.38226756, -40.57978751]	[-6.06074610e+00, -4.72330508e+00, 1.17867296e+03, -3.94131076e+00, -4.29755010e+01, 5.23510650e-01]	3	-6.060746098384669, nan, nan	1178.6729576612831, nan, nan	-42.97550103457371, nan, nan
24	64.25642169	34.18520896	-0.56606705	33.9827008	[1.81064567, 1145.06534824, -29.74138172]	[1.24642821e+00, 1.06908197e+00, 1.14412612e+03, -2.78662061e+00, -2.89398440e+01, 8.17642847e-01]	3	1.2464282146553503, nan, nan	1144.126117035637, nan, nan	-28.939843980728174, nan, nan
25	64.02659403	34.62850122	-0.52495467	33.0672572	[-2.38234259, 1111.53861969, -31.38694862]	[-1.31956404e+00, -4.75065586e-01, 1.11374779e+03, -5.99639969e+00, -3.06129953e+01, -3.06860555e-01]	3	-1.3195640380823495, nan, nan	1113.7477896293258, nan, nan	-30.61299532562568, nan, nan
26	63.9804405	34.89470736	-0.56757818	33.0709362	[-2.93504802, 1104.09505434, -29.94566796]	[-3.02503349e+00, -3.44322599e-01, 1.10168754e+03, -2.49843329e+00, -3.02063988e+01, 7.19642064e-02]	3	-3.0250334924737445, nan, nan	1101.687535910282, nan, nan	-30.20639876311414, nan, nan
27	63.50884248	34.92995869	-0.28885749	32.506027	[-30.00206745, 1073.8499205, -39.95765576]	[-27.01116262, -4.68991118, 1075.6672245, -5.13885682, -38.76023869, -1.66780427]	3	-27.011162620178148, nan, nan	1075.6672244960732, nan, nan	-38.7602386903189, nan, nan
28	63.90566815	35.36494745	-0.8143195	32.2190956	[3.2254177, 1078.41877326, -21.33653955]	[-3.13243016e+00, 4.54762483e+00, 1.07505004e+03, -2.44308172e-01, -2.43875220e+01, 2.76507310e+00]	3	-3.1324301636632086, nan, nan	1075.0500399048478, nan, nan	-24.38752196554539, nan, nan
29	63.90741636	35.8178925	-0.69802027	32.2855944	[7.67134762, 1069.97053036, -25.47136073]	[9.08468753e+00, 2.49413464e+00, 1.07042742e+03, -9.08131780e-01, -2.37057196e+01, 1.99712263e-01]	3	9.08468752579, nan, nan	1070.42741512998, nan, nan	-23.705719559769072, nan, nan
30	63.47174772	36.01645505	-0.33796565	31.4480912	[-13.38206486, 1034.2811112, -38.318896]	[-9.24455652, -3.51739366, 1038.02404926, -6.34637533, -36.47005642, -2.4865304]	3	-9.24455651995795, nan, nan	1038.0240492637924, nan, nan	-36.47005642453007, nan, nan

Figure 3: Dataset Parameter Diagram

The behavioral model forms the foundation of the entire data framework. Multiple sensor types operate synergistically to collect submarine-related data according to their respective sampling frequencies and measurement principles. The trajectory output module subsequently generates comprehensive motion trajectories by fusing submarine state estimations from all available sensors.

This module converts positional information into a unified chronological record with strict timestamp alignment, ensuring the dataset maintains a coherent time-series structure. Taking time series within the range of 1 to 29 as an example, each dataset contains the following parameters, as shown in Figure 3.

In this study, the acquired situational data variables span multiple dimensions, including Direction of Arrival (DOA) estimation, magnetic anomaly detection (Mag), positioning data, tracking information (Tracking and Track_label), and target labels. DOA estimation captures the directional angle information of incoming targets. Respectively correspond to estimated angles from Line Array 1, Line Array 2, the elevation angle of the planar array, and the azimuth angle of the planar array. A single angle corresponds to one DOA target, while three angles collectively describe three DOA targets. Mag represents magnetic anomaly detection results, while DOA provides directional estimates. The Position field contains positioning outcomes, with each column corresponding to a single target's estimated location. The Tracking component (including Track_label) records multi-target tracking results in a $6 \times 100 \times n$ format. Label data are used for target identification. Each data category comprises 100 entries, with 500 data points per entry, resulting in a total of 250,000 data points.

4.2 Data Preprocessing

The study raw dataset comprises multiple variable fields; however, issues such as data redundancy, missing values, and unstructured formats necessitate systematic preprocessing to ensure both the quality of subsequent modeling and the accuracy of predictive inference.

During data preprocessing, duplicate entries in the Direction of Arrival (DOA) and Signal variables were systematically removed, while the format of the Magnetic anomaly (Mag) variable was standardized. The textual labels in the Label variable were converted into discrete categorical features using their initial letters. For the Track_label variable, trajectory coordinates for all targets at each time step were extracted and uniformly reformatted.

To evaluate the relationship between categorical features and target labels, the chi-square test was applied. A frequency matrix was constructed based on Signal values and Label categories, from which the chi-square statistic was computed. Additionally, Spearman’s rank correlation coefficient and mutual information analysis were employed to examine variable-feature relationships. These analyses revealed that the Track_label variable exhibited consistent trends in both positional and velocity changes. To reduce dimensionality while preserving inference accuracy, only the key position-related features were retained.

The preprocessed and feature-selected multi-source dataset significantly improves the accuracy, efficiency, and robustness of the situational awareness system. This structured data foundation not only supports effective fusion of heterogeneous information but also reduces computational complexity in downstream modeling tasks.

4.3 Model Prediction Results

During model training, an early stopping strategy is implemented to mitigate overfitting. After each training epoch, the model's accuracy on the validation set is evaluated. If the current validation accuracy achieves a new historical maximum, the model parameters are saved to a checkpoint file. This optimal checkpoint is subsequently utilized during the testing or deployment phase, ensuring that the final model maintains robust generalization capability while enabling efficient and accurate performance in situational awareness forecasting tasks, as shown in Figure 4.

The confidence level distribution reflects an optimal performance pattern, with most samples exhibiting confidence values approaching 1. This indicates the model’s high degree of certainty in its predictions for such instances, demonstrating strong and reliable predictive performance, as shown in Figure 5.

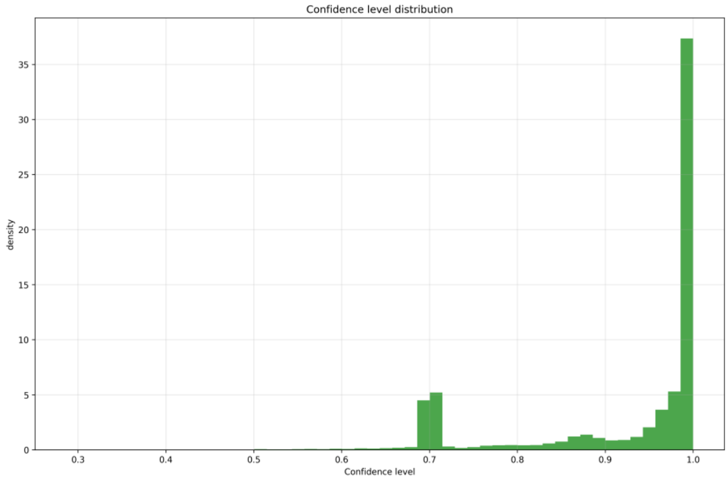

Figure 4: Confidence Interval Results Chart

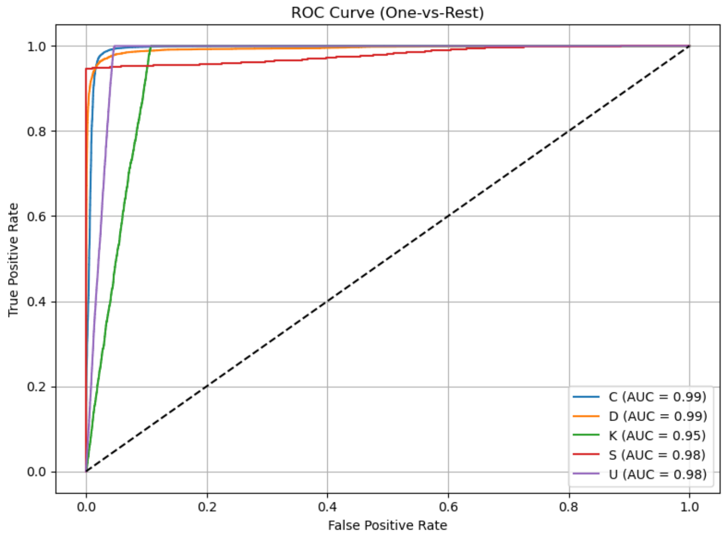

Figure 5: ROC Training Curve Results

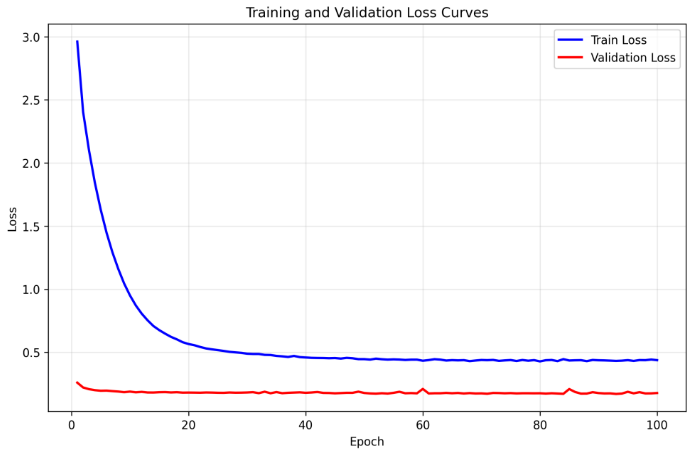

Figure 6: Training Loss and Validation Loss Convergence Curve

Within the model evaluation framework, the proposed approach demonstrates exceptional performance. The Receiver Operating Characteristic (ROC) curves for all classification categories consistently approach the upper-left corner, indicating outstanding discriminative capability. This pattern quantitatively confirms the model's robust classification efficacy, enabling precise and efficient differentiation between distinct behavioral categories. Moreover, the model maintains a high true positive rate while significantly suppressing false positives during actual classification processes, collectively reflecting the reliability and accuracy of its predictive outcomes in complex maritime environments, as shown in Figure 6.

The training loss curve reveals that throughout the entire training process, the validation loss maintained a consistently low and stable trajectory. This indicates that the model not only achieves rapid convergence but also exhibits stable performance on unseen data, effectively adapting to new samples without overfitting to the training set. These characteristics collectively demonstrate the model's remarkable generalization capacity and robust learning behavior.

4.4 Comparative Experiments and Analysis

In this experiment, performance comparisons were conducted under strictly controlled conditions: identical dataset partitioning strategies, a unified evaluation metric system, and consistent computational environments. This rigorous setup ensured the reliability and validity of the comparative analysis while eliminating potential confounding factors in model performance assessment. The superiority of the proposed method is demonstrated across multiple dimensions:

1) Comparison with Traditional Uncertainty Reasoning Methods: This includes the Dempster-Shafer (D-S) evidence theory model based on generalized uncertainty theory, standard Bayesian networks handling static probabilistic relationships, and their temporal extension, dynamic Bayesian networks.

2) Comparison with Mainstream Deep Learning Approaches: This category covers Long Short-Term Memory (LSTM) variants designed for capturing temporal dependencies.

3) Comparison with Knowledge-Driven Models: This group introduces knowledge graphs as representative structured knowledge representation frameworks.

Through comprehensive multi-dimensional comparative analysis with these highly representative model categories, this study conducts an in-depth examination from diverse perspectives and at multiple levels. This approach systematically validates the comprehensive advantages of the proposed framework in achieving effective integration of uncertain information, accurate capture of temporal dynamic characteristics, and scientific incorporation of knowledge constraints, thereby demonstrating its superior capability in complex maritime situational awareness scenarios.

Table 1: Comparison of Model Metrics

Model	accuracy	precision	recall	F1-score
Deep Bayesian Network (DBN)	94.65	92.14	91.50	91.82
D-S Theory (D-S)	90.92	91.15	90.3	90.72
LSTM neural network (LSTM)	90.87	90.31	88.85	90.55
Bayesian Network (BN)	86.76	84.89	85.57	87.2
Knowledge Graph (KG)	84.59	87.33	80.20	83.58

As shown in Table 1, the comparative results of model metrics demonstrate that the Deep Bayesian Network achieves substantial performance improvement over traditional Bayesian Networks and Dynamic Bayesian Networks. This advancement validates the effectiveness of its deep architecture in capturing complex nonlinear features and modeling temporal dynamics. Moreover, the DBN exhibits consistent and comprehensive advantages when compared with Dempster-Shafer evidence theory and Long Short-Term Memory networks, particularly in terms of recall rate, as shown in Figure 7.

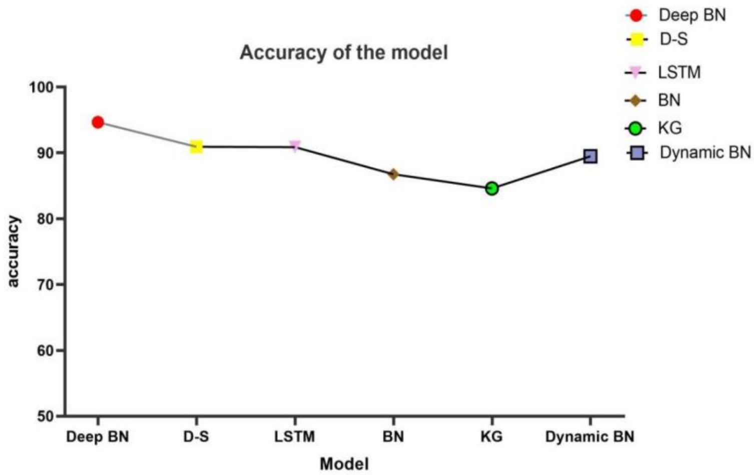

Figure 7: Accuracy Comparison Line Chart of Different Models

The line graph visually compares the prediction accuracy across different models. Results indicate that the Deep Bayesian Network achieves exceptional performance with an accuracy approaching 95%, significantly outperforming all other baseline methods and demonstrating its superior modeling and inference capabilities in complex data environments. The D-S evidence theory and LSTM models show comparable accuracy levels, delivering acceptable but relatively moderate performance. Both standard Bayesian Networks and Dynamic Bayesian Networks follow in performance ranking, while the Knowledge Graph approach yields considerably lower accuracy, indicating its limitations in direct predictive applications within this domain, as shown in Figure 8.

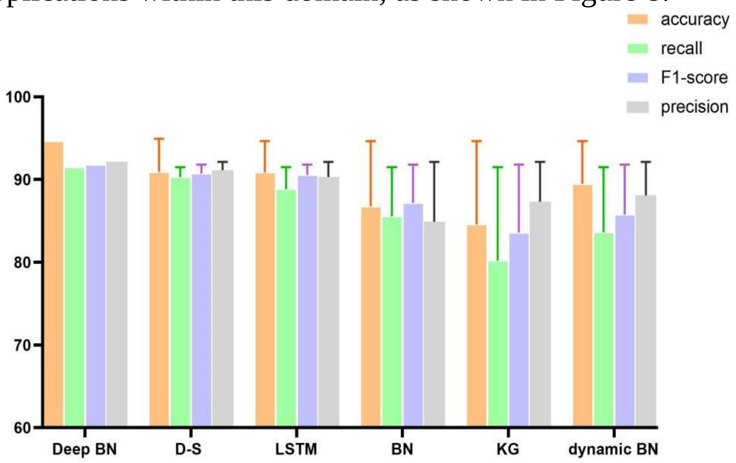

Figure 8: Bar Chart of Metric Distributions Across Models

The bar chart systematically compares the performance of different models across four key evaluation metrics: Accuracy, Recall, F1-score, and Precision. Results show that the Deep Bayesian Network achieves the highest performance across all metrics, with accuracy approaching 95%, demonstrating its comprehensive advantage in modeling complex maritime situational patterns.

5. Conclusions

We designed a novel probabilistic model centered on multi-modal fusion. Our approach fundamentally integrates Bayesian principles into deep neural networks, enabling it to not only learn from but also quantify the uncertainty inherent across diverse data modalities with varying formats, resolutions, and noise levels. By achieving principled fusion of these heterogeneous inputs, the proposed methodology attains superior predictive accuracy while providing reliable uncertainty quantification. This capability is critical for trustworthy decision support in complex maritime environments, as it offers a transparent measure of confidence in its predictions. The framework demonstrates robust performance with multisource and heterogeneous data, marking a significant advancement over conventional deterministic systems.

This integrated approach presents a promising solution for deployment across various ocean observation and maritime safety systems. Future work will focus on extending the framework to incorporate additional data modalities and enhancing its adaptability to rapidly evolving maritime conditions through continuous learning mechanisms.

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