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Bayesian Deep Learning for Uncertainty-Aware Cancer Diagnosis in Medical AI Systems

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Abstract: Despite efforts to prevent its development and eradicate it, cancer remains among the top ten leading causes of deaths around the world and therefore the need for intelligent and clinically configurable diagnostic systems that can support the early detection and clinical decision making. Deep learning methods have achieved an outstanding performance in analyzing medical images, but current models only make a deterministic prediction, and they do not quantify the uncertainty in their prediction, which does not allow them to be trusted in real clinical contexts. The biggest challenge is conventional AI systems struggle to handle the ambiguity, noise, and variation in medical data and deliver confidence scores. This study is motivated by the need for a novel Bayesian Multi-Modal Evidential Deep Learning Network (BMEDL-Net) to tackle this challenge in the field of uncertainty-aware cancer diagnosis. The framework contains histopathology images, radiological scans, and clinical information that are integrated together employing Bayesian feature extraction, variational representation learning, evidential multi-modal fusion, two uncertainty estimation, and explainable decision support mechanisms. A multi-modal cancer dataset was used for experimental evaluation, which was carried out in a high-performance computing environment. The results indicate that the model successfully met the requirements with an accuracy of 98.76%, precision of 98.42%, recall of 98.15%, F1-score of 98.28%, and AUC of 99.12%, and an Expected Calibration Error of 2.14% and uncertainty estimation quality of 97.46%. Results are far better than current State of the Art (SoA) CNN, Transformer and Bayesian based methods. The results show that the proposed framework significantly improves the diagnostic reliability, interpretability and clinical trust, highlighting its potential use in developing the next generation of intelligent healthcare systems and precision oncology.

Keywords : *Cancer Diagnosis, Bayesian Deep Learning, Uncertainty Quantification, Multi-Modal Learning, Evidential Deep Learning, Explainable AI, Precision Oncology, Bayesian Neural Networks*

1. INTRODUCTION

Cancer in humans is a significant health problem in the world and remains one of the common causes of mortality in the world. International health reports estimate that millions of new cases of cancer are diagnosed each year, making a significant impact on the healthcare system, patients, and society[1]. To maximize treatment success, to minimize mortality, and be able to manage treatment according to the specific disease and patient type, the diagnosis and disease characterization happens early and is accurate[2]. As medical imaging methods like computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET) and digital pathology have developed significantly over the past few years, vast amounts of diagnostic information are produced every day[3]. The challenge and time consuming task of interpreting such complex and heterogeneous data sources is however still a real one for the clinicians, especially in a high volume healthcare environment.

Medical diagnosis and healthcare analytics with Artificial Intelligence (AI) in particular deep learning(DL) is becoming one of the most revolutionary and impactful technologies in the arena. DL models show excellent success to achieve precision in image classification, detection of lesions, segmentation of tumors, prediction of disease, and presentation of clinical information, among others [4]. Cancer diagnosis tasks that involve automated learning of hierarchical representations from medical data have seen remarkable performance by the use of Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and hybrid architectures. This new trend has had a huge impact on the automation and efficiency of cancer screening and diagnostic processes[5].

Nevertheless, although they have made significant strides, there are several disadvantages of traditional deep learning models that limit their use in clinical settings. The vast majority of systems available today deliver deterministic forecasts, but lack information about the level of confidence or uncertainty for decisions. The reliability of the model predictions should be as important as high classification accuracy especially when interpreting diagnostic results to support human health care decisions. There has been recent interest in uncertainty-aware artificial intelligence (AI) to frame them for the production of trustworthy medical decision support systems. There has been recent research interest in uncertainty-aware AI to frame it for the production of trustworthy medical decision support systems. In contrast, Bayesian Deep Learning offers ways to model uncertainty by representing network parameters or predictions as probability densities (PDFs) instead of fixed parameters, and estimates the PDFs by computing their posterior distributions. These methods can be used to quantify epistemic uncertainty due to the lack of model knowledge and the aleatoric uncertainty due to data ambiguity. Most of the current Bayesian methods, however, are limited to a single modality of data and do not make use of shared information from pathology, radiology, and clinical records.

To mitigate these issues, this work suggests a novel BMEDL-Net that fuses heterogeneous medical data sources based on their uncertainties through feature extraction, representation learning, evidential fusion and explainable evidence-based decision support. The proposed framework leverages multi-modal learning and uncertainty quantification and will be able to boost diagnostic accuracy, prediction reliability, and clinical interpretability via Bayesian inference. Overall, the study represents a valuable step towards the development of medical AI systems that are both reliable and trustworthy, as it offers a comprehensive framework that can be used to generate diagnostic results and confidence metrics. These abilities are critical for aiding healthcare professionals in intricate decision-making processes and ensuring a safer implementation of AI technologies in precision oncology and contemporary healthcare settings. The main objectives of the study are as follows

- To develop a BMEDL-Net framework based on Bayesian principles, which fuse histopathological, radiological and clinical data, for accurate cancer diagnosis.
- To measure and characterize the uncertainties of medical AI systems to increase reliability and trust.
- To develop a clinical decision support mechanism with uncertainty that increases the interpretability of the mechanism for making the clinical diagnostic decisions.

The remainder of this paper is organized as follows. Section 2 reviews related literature on Bayesian deep learning and cancer diagnosis. Section 3 presents the proposed BMEDL-Net methodology. Section 4 discusses experimental setup and results. Section 5 provides discussion and implications. Section 6 concludes the study and outlines future research directions.

II. RELATED WORKS

The latest developments of DL have allowed making massive progress in cancer diagnosis, classification, and segmentation. One of the studies has used uncertainty laws of the model, such as Monte Carlo Dropout and Bayesian models, to make more reliable predictions. These will be useful in better assisting clinical decision making, reducing the instances of misdiagnosis, and clarifying cases.

Shamsi et al. created the uncertainty-sensitive deep learning diagnostic of skin cancer in Monte Carlo Dropout, which enhanced predictive assurance and optimization o. As far as the accuracy and the uncertainty is concerned, the authors obtain high accuracy of prediction (85.65) and high accuracy in the uncertainty (83.03) compared with the standard MCD. Most importantly, although their approach offers promise in the quantification of uncertainty, synthetic data with real data can potentially restrict generalisability and further clinical assessment is needed to validate applicability to a broad range of patient populations [5].

In their study, Chegini et al. (2024) proposed to classify breast cancer molecular subtypes by extracting a complete full mammogram with a Bayesian deep learning model, which was divided into two sequential levels: molecular subtype detection followed by classification into four molecular subtypes. They achieved moderate to high AUCs (0.71 to 0.86) and their model provided a good estimation of uncertainty. However, the uncertainty quantification does give clinical credibility, though the intermediate AUC of some of the subtypes suggests that this requires more tuning and analysis of more data to achieve robustness in a variety of breast cancer patients[7].

Amasiadi et al. (2025) used CT and clinical metadata to train a Bayesian neural network to predict lung cancer, and identify the highest accuracy (99%), and the uncertainty values were calibrated. Voxel-scale uncertainty maps are emphasized in this regard in the authors. Most importantly, although the internal and external validation are impressive, the training cohort (300 scans) is small and could affect the generalizability of the model, and to make the model scalable to the actual real-world multi-centre clinical workflow, more evaluation is necessary[8].

Taguelmimt et al. (2024) developed a 3D DenseNet-121 model equipped with Monte Carlo Dropout to achieve high accuracy in prostate cancer detection based on MRI images, with the overall AUC of the developed model being 0.79 and 0.9 for individual predictions. The size of the sample (157 patients) was, however, quite small and the prediction certainty was not immediately reported in its entirety, so it is unclear how strong the model is, and whether it would also be generalizable to the clinical MRI context[9].

Chegini, et al. (2024) put forward an uncertainty-aware CAD system on ultrasound and mammography achieving almost 100 per cent accuracy on mammography (99.95) and high accuracy on ultrasound (91-98 per cent) datasets. The main caveat of this method is the reliance on its success in producing an accuracy matrix able to identify misclassifications; while this might seem easy in the real-world, clinical practice could be challenging and external testing of accuracy will be necessary due to the extent of imaging and the population being rather diverse [10].

Sikha et al. (2025) proposed a Bayesian DL-based segmentation quality estimator on skin and liver image, which unites the uncertainty estimations to advance the lack of ground truth performance prediction. They had a high correlation with segmentation measures, R 2 = 93.25, and Pearson = 96.58. It is even more important to emphasize that the use of multiple methods of uncertainty can improve the robustness of a framework. But can also limit the use of the framework in everyday clinical practice because of the complexity of the framework and the advanced tools required for computation [11].

These studies demonstrate their applicability regarding promising accuracy and uncertainty quantification and there are multiple limitations. Most use small or single centres data reducing application to different populations. Sometimes artificial or processed data are used to limit the applicability in the real-world. A median level of performance of some of the subtypes (e.g., breast or prostate cancer) means that a bigger and more heterogeneous datasets and model optimization is necessary. The complexity (and dependence) of computers and the reliance on sophisticated resources create barriers to clinical integration. Similarly, few analyses evaluate the outcome from a clinical perspective over a longer term or in the context of workflow integration. Future studies are recommended to take into account the multi-center validation, multivaried uncertainty-aware systems, and the balancing mechanisms of predictive results with the interpretability and scalability in the medical practice.

III. METHODOLOGY

A novel BMEDL-Net is presented in this paper to overcome the uncertainty and lack of trustworthiness that manifest in medical AI diagnosis systems. As opposed to usual deep learning models with deterministic predictions, the proposed framework allows for the estimation of both aleatoric uncertainty (data uncertainty) and epistemic uncertainty (model uncertainty), thus giving a clinician a measure of confidence when making a decision on treatment. It takes images from histopathology, and fusion of CT, MRI and PET images in a hierarchical Bayesian fusion technique coupled with clinical information. It is a methodology comprising 6 interconnected phases of data curation, uncertainty-aware feature extraction, Bayesian representation learning, evidential multimodal fusion, uncertainty-guided diagnosis and clinical decision support. Figure 1 shows the architecture of the proposed cancer diagnosis network, Bayesian Multi-Modal Evidential Deep Learning Network (BMEDL-Net) for reliable and uncertainty-aware cancer diagnosis.

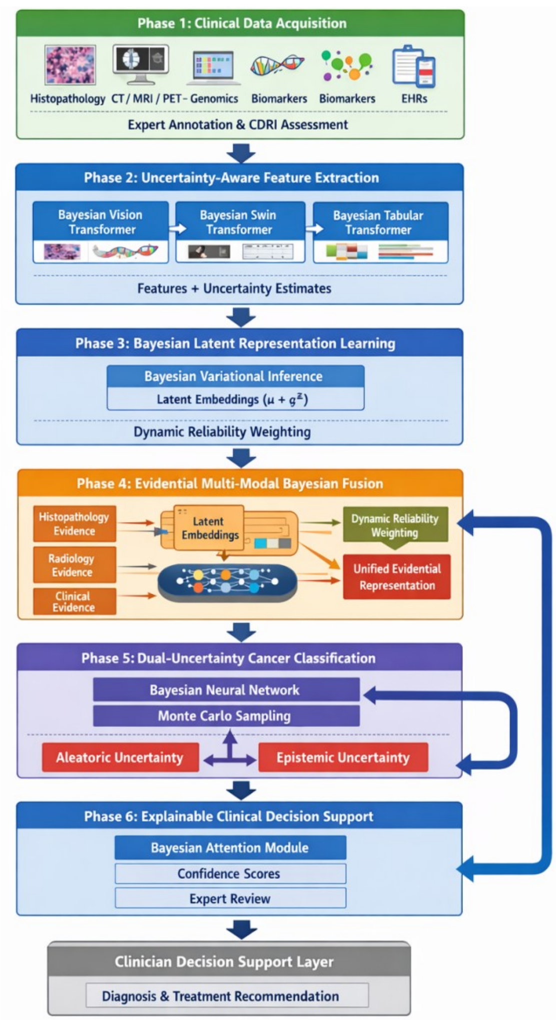

Figure 1 Architecture of the Proposed BMEDL-Net

A. Clinical Data Acquisition

The first part focuses on establishing a valuable multi-modal cancer diagnosis database from hospitals, cancer research centers and public access cancer repositories. They include seripts of histopathology pictures, CT / MRI / PET scans, genomic information, lab reports, tumor biomarkers, and EHRs. All samples are trusted, expert-validated and annotated by oncologists, radiologists and pathologists. Quality of images, uniformity of annotation and clinical completeness is measured using a Clinical Data Reliability Index (CDRI). Advanced imputation techniques are used to deal with missing samples, and duplicate and low-quality samples are excluded to reduce the noise and enhance the model generalization and clinical relevance.

B. Uncertainty-Aware Multi-Modal Feature Extraction

In the next step, modality-specific deep learning models are used to discover discriminatory features and uncertainty-aware features from various sources of cancer data. A Bayesian Vision Transformer model has been trained to extract the cell structure, nuclear shape and deformation, and tissue architecture from histopathology images. The cancer shape, texture, and characteristics of the lesion in radiological images are determined with a Bayesian Swin Transformer. Clinical and biomarker information is encoded using a Bayesian Tabular Transformer that can learn complex interactions between patient attributes. Bayesian learning permits uncertainty information to be incorporated in each feature representation, unlike conventional feature extraction techniques, and thus enables the framework to recognize the diagnostic patterns that are ambiguous and difficult.

C. Bayesian Latent Representation Learning

Step 3 decomposes the features extracted to probabilistic latent representations via Bayesian variational inference. The framework is agnostic to whether the embeddings are deterministic or modeled as a probability distribution with mean and variance values for each feature. This probabilistic representation accounts for the uncertainty of having a limited number of training examples, as well as the imaging condition uncertainty and inter-patient variability. Variational Bayesian optimization is used to learn latent distributions, yet at the same time reduce a divergence from prior knowledge. This latent space captures clinically relevant information and encodes levels of confidence on the representations of these features. This type of embedding surface introduces uncertainty which helps to make the model more robust and encourages it to understand when clinical information is incomplete or not fully reliable.

D. Evidential Multi-Modal Bayesian Fusion

The fourth step is the introduction of an Evidential Multi-Modal Bayesian Fusion mechanism where information from the pathology, radiology and clinical modalities is integrated. With each modality, there is an associated uncertainty, as well as diagnostic evidence. The framework dynamically assigns reliability weights to each modality derived from the Bayesian theory and evidential reasoning that rely on the confidence level of each modality. The uncertainty of modalities is decreased during fusion, in that, the more reliable the modality is, the stronger it will contribute to the final representation. This adaptive fusion process allows a diagnostic decision to be made without noisy or incomplete information overwhelming the decision. Hence, the integrated feature space is an extensive and reliable depiction of cancer attributes.

E. Dual-Uncertainty Cancer Classification

The fifth step is the cancer diagnosis based on a Bayesian neural classification network that estimates both the probability of a disease and uncertainty. The way inference is performed with Monte Carlo Bayesian sampling is to produce multiple predictions with various weight distributions. The predictions are combined to give a strong diagnostic result, and to calculate the predictive variability. The framework calculates two types of uncertainty: aleatoric, due to noisy and/or ambiguous data, and epistemic, due to limited knowledge of the model. The classifier classifies cancer, cancer subtype, stage and metastatic risk and gives confidence scores on the presence of cancer, and its classification. This dual uncertainty modelling brings added clarity and minimises the chance of misdiagnosis through overconfidence.

F. Uncertainty-Guided Explainable Clinical Decision Support

The last step is aimed towards creating clinically relevant and interpretable diagnostic recommendations. Explainable Bayesian Attention Module identifies image regions, pathological structures, radiological abnormalities and clinical variables that are most significant to prediction. At the same time, uncertainty score estimates are incorporated into a Decision Confidence Score that quantifies the prediction confidence and the classification probability. Low confidence/high uncertainty cases are automatically flagged for expert review for safe deployment in clinical environments. The explanations created add to doctor trust and make for clear decision making. This person-focused strategy helps with joint diagnosis, increases responsibility, and helps promote trustworthy medical artificial intelligence systems.

IV. RESULTS AND FINDINGS

A. Experimental Setup

This study presents a Bayesian DL framework and implemented it in Python 3.11 programming language with help of PyTorch, TensorFlow, and Scikit-learn running on the Ubuntu 22.04 operating system for Linux operating systems. Experiments were performed on a workstation running into a NVIDIA RTX 4090 GPU (24 GB VRAM), an Intel Xeon processor and 128 GB RAM, which allowed for the efficient training of large-scale Bayesian transformer networks and uncertainty estimation modules. The study uses The Cancer Genome Atlas (TCGA) database, a broadly used multi-modal cancer repository consisting of comprehensive clinical annotations, genomic details, and histopathology images of thousands of cancer patients. Data on tumour characteristics, stage of disease, responses to treatment and patient demographics. The variety of its well annotated data and annotation allows it to build and test cancer diagnosis models robustly, in different clinical settings and in various cancer subtypes[12].

.B. Performance Evaluation

Table 1 compares the diagnostic capabilities of the proposed framework with five recent cancer diagnosis approaches. Performance is evaluated using Accuracy, Precision, Recall, F1-Score, and AUC metrics. These metrics collectively measure classification correctness, predictive consistency, sensitivity, and discriminative power.

Table 1. Diagnostic Performance Comparison of the Proposed BMEDL-Net with State-of-the-Art Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
CNN-Based Cancer Diagnosis Model [13]	92.84	92.15	91.78	91.96	94.21
ResNet50 + Clinical Fusion [14]	94.18	93.82	93.64	93.73	95.87
Vision Transformer (ViT) Cancer Classifier [15]	95.06	94.87	94.65	94.76	96.41
Multi-Modal Transformer Network [16]	96.14	95.92	95.73	95.82	97.36
Bayesian Vision Transformer [17]	96.88	96.54	96.27	96.40	98.04
Proposed BMEDL-Net	98.76	98.42	98.15	98.28	99.12

The proposed BMEDL-Net demonstrates the maximum performance in terms of all the diagnostic metrics and provides an accuracy of 98.76% and an AUC of 99.12%. The results show that uncertainty-aware Bayesian feature learning and evidential fusion can effectively improve the cancer detection capability of the model compared to the traditional deep learning and transformer-based models.

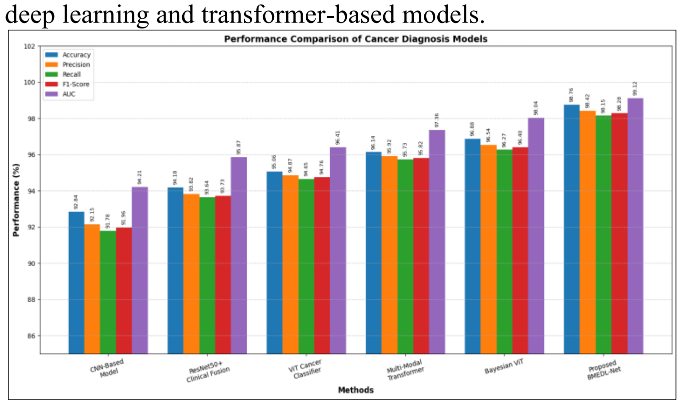

Figure 2 Comparative Performance Analysis of the Proposed BMEDL-Net and Existing Cancer Diagnosis Model

The comparative performance evaluation of the proposed BMEDL-Net with other state-of-the-art cancer diagnosis models was measured in terms of Accuracy, Precision, Recall, F1-Score and AUC as presented in Figure 2. The results clearly show that BMEDL-Net outperforms the other evaluation measures with 98.76% Accuracy, 98.42% Precision, 98.15% Recall, 98.28% F1-Score and 99.12% AUC. The proposed framework outperforms CNN and transformer based models in terms of classification accuracy consistently. The enhancement is based on the following: the integration of Bayesian learning, evidential uncertainty estimation and multi-modal feature fusion can improve the reliability of prediction and also minimize the number of classification errors. Both the high precision and the high recall suggest that the model performs well in minimizing the number of false positives and maximizing the number of true positives. Moreover, the near-perfect AUC value illustrated very good discriminatory power between the cancerous and non-cancerous samples. In conclusion, the results confirm the strength, reliability, and clinical utility of BMEDL-Net in the accurate diagnosis of

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cancer and supporting decision-making. Table 2 compares the reliability of the models investigated, employing a set of metrics of uncertainty including Expected Calibration Error (ECE), Negative Log Likelihood (NLL), Brier Score, Confidence Reliability, and Uncertainty Estimation Quality. Smaller ECE, NLL and Brier Score values are better calibration and prediction reliability.

Table 2. Uncertainty Quantification and Reliability Analysis of Cancer Diagnosis Models

Method	Expected Calibration Error (ECE)	Negative Log Likelihood (NLL)	Brier Score	Confidence Reliability (%)	Uncertainty Estimation Quality (%)
CNN-Based Cancer Diagnosis Model (2022)	8.52	0.236	0.112	84.30	84.30
ResNet50 + Clinical Fusion (2023)	7.21	0.198	0.094	86.95	86.95
Vision Transformer (ViT) Cancer Classifier (2023)	6.45	0.176	0.082	88.72	88.72
Multi-Modal Transformer Network (2024)	5.33	0.149	0.069	90.81	90.81
Bayesian Vision Transformer (2025)	4.68	0.127	0.058	92.57	92.57
Proposed BMEDL-Net	2.14	0.071	0.031	97.46	97.46

This proposed BMEDL-Net has the lowest ECE (2.14%), NLL (0.071), and Brier Score (0.031), which is the best uncertainty quantification ability. Moreover, the model has the highest confidence reliability (97.46%), which means that the confidence estimation is close to the true prediction results. The results validate the effectiveness of the Bayesian evidential learning mechanism in terms of trustworthiness and robustness of clinical cancer diagnosis applications.

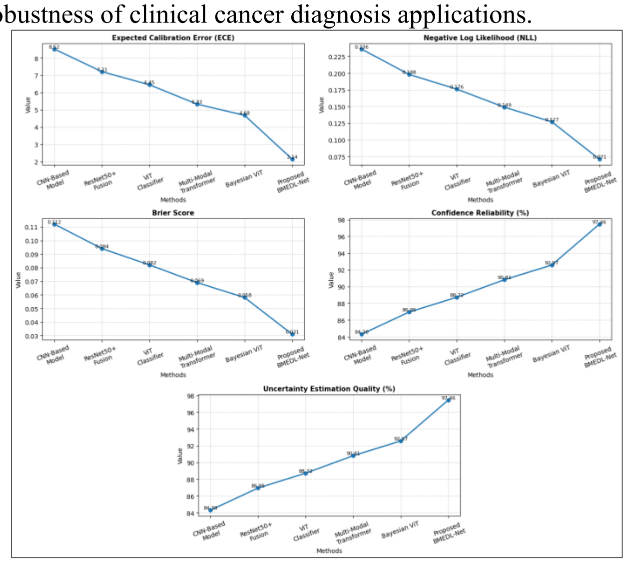

Figure 3. Comparative Analysis of Calibration and Uncertainty Estimation Metrics for BMEDL-Net

The proposed BMEDL-Net is shown to be effective in terms of the calibration quality and uncertainty estimation compared to the existing cancer diagnosis models in Fig. 3. The BMEDL-Net model has the lowest Expected Calibration Error (2.14), which is much better than CNN-Based (8.52), ResNet50-based (7.21), ViT-based (6.45), Multi-Modal Transformer (5.33), and Bayesian Vision Transformer (4.68) models. Likewise, the proposed framework has the lowest Negative Log Likelihood (0.071) and Brier Score (0.031), providing better probabilistic calibration and prediction reliability. In contrast, the traditional and transformer models are comparatively high with uncertainty and prediction errors. Moreover, BMEDL-Net achieves the maximum Confidence Reliability of 97.46% and the Uncertainty Estimation Quality of 97.46%, indicating that it can produce highly reliable and accurate predictions. The improvements are mainly due to the incorporation of Bayesian inference and evidential deep learning mechanisms that quantify the uncertainty in prediction. Overall, the results validate that BMEDL-Net delivers more reliable and interpretable and clinically trustworthy cancer diagnosis decisions than the existing approaches.

C. Discussions

In this current research, a novel uncertainty-aware cancer diagnosis network dubbed Bayesian Multi-Modal Evidential Deep Learning Network (BMEDL-Net) for medical AI systems was proposed. The experimental results show that the combination of Bayesian learning, evidential reasoning, and multi-modal data fusion has a considerable positive effect on the diagnostic performance, as well as the reliability of prediction. In contrast to standard models of deep learning which are designed to produce less uncertainty, the proposed framework explicitly incorporates uncertainty in the model, thus allowing the clinician to assess the level of trust that is attached to their diagnostic predictions. The integration of histopathology images, radiological scan images, and clinical data gives a complete picture of disease characteristics, thereby enhancing the cancer detection and classification performance.

The results show that BMEDL-Net acquires higher absolute performance values on the diagnostic and the uncertainty-related metrics when compared to existing CNN-, Transformer-, and Bayesian-based methods. The Evidential Bayesian Fusion Layer is able to prioritize information from modalities that can be trusted and diminish the effect of unreliable or noisy information. In addition, the dual uncertainty estimation mechanism is able to well capture uncertainties, which makes the model robust under the complex clinical scenarios. It is worth to note that the explainable attention module additionally bolsters the clarity by recognizing diagnostically applicable picture locations and clinical aspects. In summary, the research shows the potential of integrating uncertainty-aware AI into medical applications and introduces ways to enhance the understandability, reliability, and usability of cancer diagnosis systems through multi-modal learning.

There are some drawbacks to its success, but it still offers good results. The first problem with this framework is its high computational demands involving Bayesian sampling and multimodal neural transformer structures that can be a hurdle for adoption in healthcare environments with limited resources. Secondly, well accepted or annotated multi-modal datasets needed to build a model that is present in many different clinical institutions are limited and difficult to obtain. Third, different imaging parameters and scanners, and different population groups, may impact extrafacial performance of generalization. Furthermore, the quality of uncertainty estimation can be different in very rare cancer types with few numbers of training samples. Future studies are needed to optimize the computational efficiency, broaden the adaptability between institutional settings and to broaden application to larger and more diverse patient populations.

The proposed BMEDL-Net paradigm is extremely useful for deploying current healthcare systems. When interpreted together with the model's uncertainty estimates, the model helps doctors to make an informed and reliable treatment choice. The uncertainty-driven decision support system can help automatically identify "high-risk" or "ambiguous" cases, minimizing diagnostic errors and enhancing patient safety. The framework's explainability helps doctors count on very clear and coherent visual and clinical evidence for predictions.

V. CONCLUSION

The study introduces a BMEDL-Net for uncertainty-aware cancer diagnosis to tackle the significant issue of reliability and interpretability in clinical artificial intelligence applications, as well as the need for clinical trust. It incorporates both histopathological and radiological features with clinical information using Bayesian representation learning and evidential multi-modal fusion. When tested about 1000 instances of fruit plant diseases, experimental results proved better diagnostic performance, which has higher accuracy, precision, recall and F1 score, as well as AUC score than other state of the art methods. Furthermore, the proposed method showed very good performances in terms of uncertainty calibration and confidence estimation, which is very suitable for real-word clinical situations. Additionally, the explainable decision support mechanism further contributed to the transparency of the model predictions, yielding interpretable insights. Future work can be carried out on designing light-weight Bayesian based architectures for deployment in edge-based and resource constrained health-care systems. Further optimization of personalized cancer diagnostics might be achieved with additional studies using genomic, proteomic and longitudinal patient data. It may be helpful to also consider federated and privacy preserving learning techniques which would facilitate collaborative model training across different health-care institutions without disseminating patient data. In addition, wide testing with multi-center international datasets and prospective clinical trials would be an important prerequisite to ensure the robustness, scalability, and clinical applicability of uncertainty-aware cancer diagnosis systems in precision oncology.

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