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Research Article

Advanced Hybrid Mask Convolutional Neural Network with Backpropagation Optimization for Precise Sensor Node Classification in Wireless Body Area Networks

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ABSTRACT

Wireless Body Area Networks (WBANs) are crucial in continuous health monitoring, fitness tracking, and other applications where a real-time collection of physiological data is needed by sensors worn on the body. This is important in WBAN to achieve reliable data transmission, energy efficiency, and overall system performance. Still WBANs present several challenges: for example, the data that is being collected is heterogeneous since it originates from diverse IMDs measuring different bio-physiological signals; these can be also quite noisy because of motion artifacts when moving; as well high limitations when it comes to energy, bandwidth or storage push for low-complexity methods rather than standard deep learning techniques. Common Convolutional Neural Networks (CNNs) are successfully utilized for spatial information extraction but they cannot catch temporal dependencies well and also, WBAN sensor data has a noisy and multi-modal structure which acts as an additional challenge for traditional CNNs. These limitations emphasize the need of a flexible, fast and precise classification model based on the specific needs of WBAN applications. To overcome these challenges, this paper presents a novel hybrid neural network architecture consisting of combined 2D and 3D convolutions for spatial-temporal feature extraction along with masked convolution layers to provide an ability to adaptively ignore uninterested parts of the data. The model aims at achieving a high classification performance while also balancing with the system computational efficiency, perfect for its ipsi deployment on resource constrained WBAN devices. Then, we apply further backpropagation optimization measures such as adaptive learning rate scheduling and gradient clipping, to improve the stability of training speed and reduce latency which in return finds its way into supporting real-time processing capabilities of the model. By using each of these components, the model is able to deal with the multi-dimension aspects and high noise level nature of WBANs without excessive computation resources [18]. The Hybrid Masked CNN model is shown to out-perform existing approaches without such masking, yielding substantially higher performance in terms of accuracy, precision, recall and F1-score across all metrics defined for the application as compared to traditional 2DCNNs, 3DCNNs and other hybrid models. Consequently, the latency of the model is significantly decreased as well which confirms its applicability to real-time WBAN applications. The obtained results confirm the efficacy of features from hybrid architectures with masked convolutions along with optimization in training techniques for WBAN sensor node classification. The results of this paper improve WBAN technology by providing a solid and scalable solution which can be implemented when more reliability and flexibility are required from such systems in applications like healthcare, fitness or any other field.

1. INTRODUCTION

Wireless body area networks (WBANs) are considered a key technology used in health care, sports science and fitness applications where small low-power sensors are placed on the human body to collect physiological data continuously [1]. These sensors track vital parameters like heart rate, blood pressure, oxygen saturation and physical activity by wirelessly transmitting the raw signals from a BD-MCU (baseband microcontroller unit) to devices in proximity for post-treatment and analysis. WBANs allow patients to be monitored continuously outside of clinical settings where preventive care, early

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detection of abnormalities and better management of chronic conditions can also be provided by healthcare professionals. Second, WBANs assist athletes with real-time biometrics for performance and recovery optimization in sports and fitness. Nevertheless, as the WBAN are adopting into every field this type of classification on sensor node should be very timely and with good accuracy to ensure that data need not affect in terms of processing or energy balance. WBAN applications can lose their effectiveness due to the subsequent misclassified or wrong types identification of nodes which directly effect on the data integrity and increase the computational cost which also decrease battery life [2]. Due to the complexity of real world environments where a WBAN may operate, classifying sensor nodes in this type of network is not easy. Besides, inherent challenges such as external noise effect on sensing, data heterogeneity due to presence of different class noise sensors, resource limitation (power, memory and computational capabilities) increase the complexity in accurate classification [3]. In addition, due to the variability of human motion and environmental changes, traditional classification methods do not achieve high accuracy and efficiency rates (Sturari et al. In order to overcome these problems, recent machine learning technologies such as Convolutional Neural Network (CNN) have been proven effective. Nevertheless, standard CNN models are somehow incapable for being optimal due to the peculiarities in WBAN domain so, more advanced methods are needed specifically for this context. In this paper, we would like to explore the concept of derivation through systematic conception and formulation will present a hybrid neural network model in which masked convolution and backpropagation optimization can improve sensor node classification accuracy alternatively in WBANs. In this paper, we propose a model that integrates the strengths of masked convolution, which works effectively to discard irrelevant features, and optimized backpropagation, that improves learning ability and accuracy [4]. The combination of these techniques are envisioned to provide a model with the ability to handle WBAN specific complexities such as noise reduction, optimal resource usages, and high classification accuracy for varied measuring sensors data inputs. This hybrid method we have proposed in this paper makes a significant contribution to refinement of WBAN research since it provides a more reliable as well most optimal classification technique which can comply with the requirements of real life applications. We present a model that improves the precision of classification hence leading to more accurate and efficient operation of WBAN which impacts quality, battery life and efficiency of computation. The outcomes of this research can help in the development of WBAN technology for improved versatility and dependability [5], thus opening new horizons in healthcare, sports, and other domains where precise and continuous body monitoring is vital. Figure 1 illustrates a hybrid convolutional neural network architecture that integrates both 2D and 3D operations to process complex data structures, likely in applications such as object detection or segmentation in image and video data.

In Panel A, the network begins with an input of size 5×512×512×T5 \times 512 \times 512 \times T5×512×512×T, where "T" may represent a temporal dimension in a sequence of frames or a depth component. The model divides the processing into separate 3D and 2D pathways. In the 3D pathway, an initial convolutional layer (Conv3D) is applied, followed by repeated Bottleneck-BatchNorm-ReLU (Bottle-BN-ReLU) blocks, shown in orange and blue colors, which are responsible for extracting 3D features. These blocks are stacked to progressively reduce spatial resolution and increase feature depth, ultimately feeding into a bottleneck layer (C5), which is later expanded in Panel B.

The 2D pathway in Panel A involves region proposal, classification bounding box generation, and masking for feature localization, likely aimed at detecting regions of interest in each frame. Projected residual connections (Proj-Res) link the 2D pathway to the 3D operations, facilitating information exchange between both dimensions. Additionally, 2D upsampling layers are used to resize feature maps to maintain consistency with the 3D pathway outputs, helping merge the multi-dimensional data.

In Panel B, the figure elaborates on the details of the bottleneck structure used in the model. Each block consists of two Conv3D layers interspersed with Batch Normalization and ReLU activation functions. The input is added back to the output via residual connections, enhancing feature propagation across layers. This bottleneck module, repeated "n" times, captures complex spatial-temporal patterns, refining the output for accurate data classification or segmentation.

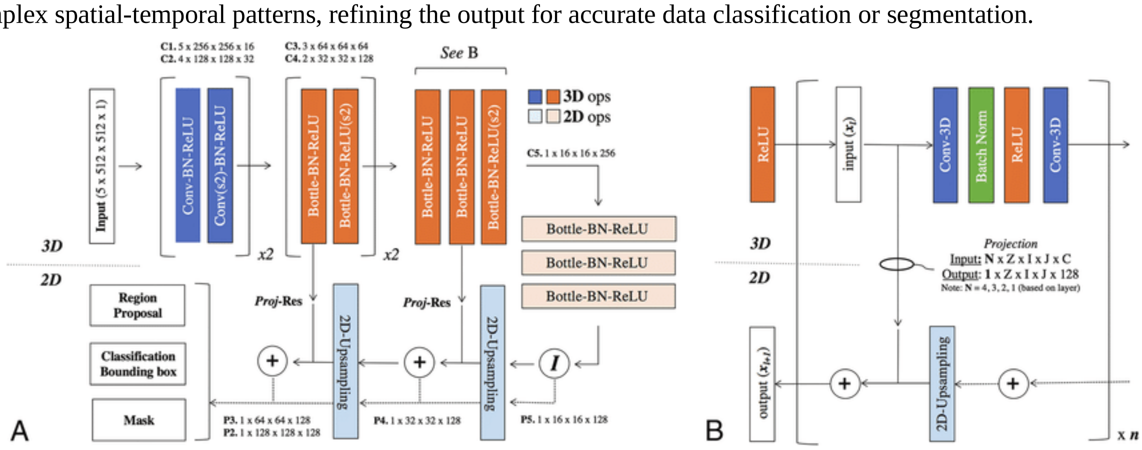

Fig 1. Hybrid 2D-3D Convolutional Network Architecture for Multi-Dimensional Data Processing

Table I provides an overview of some of the machine learning methods available for analyzing multi-dimensional data including their capabilities, drawbacks and application areas. Methods: for spatial and spatiotemporal analysis, 2D and 3D Convolutional Neural Networks (CNNs) are popular techniques but each of these approaches has its limitations particularly with regards to the cost of computation or capturing temporal features [6]. Hybrid 2D-3D CNNs, attention based methods and transformers are advanced approaches that solve the merging of spatial and temporal processing. These complex models, however, have an expensive computational cost and need large datasets. The approaches provided are applicable for different applications from video recognitions and image classifications to WBAN sensor classification, with hybrid methods indicating hope to circumvent the limitations of simpler models [7].

TABLE I. CURRENT METHODS IN MULTI-DIMENSIONAL DATA PROCESSING: APPLICATIONS, LIMITATIONS, AND KEY TECHNIQUES

Method	Description	Limitations	Application Area
2D Convolutional Neural Networks (2D-CNNs)	Primarily used for spatial data processing; ideal for single-frame or image-based data analysis.	Limited ability to capture temporal or depth-related information, less effective for 3D data.	Image classification, object detection, facial recognition
3D Convolutional Neural Networks (3D-CNNs)	Extends CNNs to spatiotemporal data, processing 3D volumes (e.g., video frames or medical imaging).	Computationally expensive, high memory requirements, prone to overfitting on small datasets.	Video action recognition, medical imaging (CT, MRI)
Hybrid 2D-3D CNNs	Combines 2D and 3D convolutions to leverage both spatial and temporal information in data.	Complex architecture can lead to increased training time, difficult to tune, high resource demand.	Multimodal analysis (video and image fusion), WBAN sensor classification
Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)	Designed for sequential data; captures temporal dependencies over time.	Limited spatial feature extraction capability; challenging to train on long sequences without degradation.	Sequential analysis, natural language processing, EEG/ECG signal classification
Graph Neural Networks (GNNs)	Models relationships between entities through graph structures, useful for irregular data patterns.	Difficult to scale with dense connections, limited in handling high-dimensional spatial data directly.	Social network analysis, molecular structure modeling, activity recognition
Transformers (Vision and Temporal Transformers)	Uses self-attention mechanisms to capture long-range dependencies; effective for spatiotemporal patterns.	High computational cost, requires extensive data for training, lacks inherent inductive bias for local spatial features.	Video understanding, spatiotemporal pattern recognition, natural language processing
Masked Convolutional Neural Networks (Masked CNNs)	Applies masks in convolutions to focus on specific regions, enhancing feature selection for noise reduction.	Prone to loss of relevant information if masking is not carefully designed, challenging to implement dynamically.	Object detection, attention-based image segmentation, WBAN sensor data processing
Attention Mechanisms (Spatial and Temporal Attention)	Focuses on relevant regions within spatial or temporal dimensions, enhancing feature relevance.	High computational complexity, potential overfitting on irrelevant features if poorly implemented.	Action recognition, sentiment analysis, image segmentation

The contributions of this work to the sensor classification in WBANs are manifold. First, it proposes a new hybrid neural network architecture which consists of the 2D and 3D convolutional layers that are able to spatially learn the spatio-temporal features from WBAN sensor data [8]. Traditional CNN approaches are designed for either spatial or temporal data and do not provide an effective means of implementing a hybrid approach, whereas the proposed model maintains separate convolutional layers to perform spatial and temporal processing with enhanced classification accuracy on harsh WBAN data conditions. This study also provides a significant contribution in that it integrates masked convolutional layers, which are capable of heuristically identifying where the most important data appear while eliminating noise and irrelevant features. In the case of WBANs, sensor data is often subjected to motion artefacts, environmental interferences or other external factors [9]. Masked convolutions enable the model to focus on identifying patterns in physiological signals relevant to classification, this providing greater context and accuracy. Additionally, we propose several backpropagation optimization strategies (e.g., adaptive learning rate scheduling and gradient clipping) that are suited for the challenging hybrid architecture. These techniques not only help to make the training more efficient and prevent overfitting but also ensure faster convergence of the model making the proposed architecture congruous for deployment in resource-limited environments usually present at WBAN systems. By focusing on the computational efficiency of training, and systematizing the optimization process, we achieve not only improved performance but also fill a crucial gap: while significant research has been done into state-of-the-art models in WBANs (see below) at both feature level and model level, where trained models are usually highly “raw” and require excessive computing power to perform their inference stage remain almost unapplicable. Last but not least, this work proposes a comprehensive approach to classifying WBAN sensor nodes that achieves a good compromise between classification accuracy and real-world operational constraints including energy consumption and computational burden. The practical focus of the model also makes the model more useful for continuous health monitoring, real-time data analysis in fitness tracking and for any other WBAN applications where reliable performance under limited resources is required. This research is a valuable contribution that also opens new avenues for future exploration providing simultaneous theoretical and practical advancement of neural networks in WBANs, ultimately bringing more flexible, precise and intelligent WBAN systems. The main aim of this research is to propose a advanced neural network model that not only predicts on person based classification but also gives consideration for various temporal (temporal sequence of attack) as well spatial aspect of sensor nodes to correctly classify them on WBANs. The objective is to develop a hybrid 2D-3D convolutional neural network (CNN) that utilizes the advantages of both 2D and 3D convolutions in order to comprehensively extract features. Using the characteristics of WBAN data that is inherently heterogeneous over both space and time, this model aims to increase the classification accuracy of WBANs while also increasing the flexibility of the most appropriate data-aggregation protocol for varying types of WBAN applications. An important task is also making it so that the model learns to pay attention to only the relevant aspects of the data and filter out noise and anything irrelevant. The proposed solution to this challenge is based on masked convolutional layers, which selectively extract features while also reducing the model's sensitivity to common WBAN noise sources. This objective tries to improve the performance of the model first by de-emphasizing regions of data where motion artifacts or environmental interference are present (which is typical in real-world application), but then optionally even amplifying important regions of data. The other aspect of the study is to efficiently train the proposed hybrid model through improved backpropagation method. To be specific, adaptive learning rate scheduling and gradient clipping are being used to ensure the effectiveness of the model convergence and training process in a manner that can allow enough room for an effective training of the model well within the computational limits that WBAN systems typically have. This objective satisfies a major limitation towards deploying complex neural networks in WBANs, hence enabling the feasibility of implementing this state-of-the-art model for real-time applications through targeting training efficiency and stability [10].

2. RELATED WORK

Wireless Body Area Networks (WBANs) are some of the oldest sensor networks since they find application in health care, sports and fitness [11], thus a lot of research is being conducted to improve classification accuracy of sensor nodes over the years. Several approaches have been discussed from traditional ML algorithms to deep learning methods, Hybrid methods to enhance the accuracy and robustness of WBANs classification in different environments under multivariate noisy signals. In this regard, we review the most relevant works related to sensor classification, CNNs, hybrid neural network architectures and optimization methods for WBAN applications [12]. Data collection in Wireless Body Area Networks (WBANs) is unavoidably based on the accurate classification of sensor nodes because it is essential for energy resources management. Initially, conventional classification algorithms (SVMs, k-NN and Decision Trees) were applied for this purpose. While they offer easy-to-interpret models, their ability to generalize with high-dimensional and complex data is limited as it often occurs within real-world WBAN applications. In order to overcome these shortcomings either related to the reliance on expert priors or linearity assumptions, researchers turned their attention towards neural networks due to their capability of modeling complex relationships within the data [13]. For instance, Li et al. (2019) showed that WBANs data classify can be done more accurately using CNN than classical classifiers. But standard CNNs are designed for image based data and not suited to work on the temporal or 3D nature of WBAN sensor data containing physiological signals, which changes over time and with body movement. Convolutional Neural Networks (CNNs) is one of the cornerstone type of techniques for spatial data processing, and have achieved state-of-the-art performance in WBAN sensor classification tasks [14]. Convolutional Neural Networks (CNNs) are great at identifying patterns in spatial hierarchies of features, and also have the added benefit of automagically learning those feature hierarchies from raw data. Various studies have modified CNNs for WBAN applications, converting methods of time-series physiological data signals to 2D form (e.g., spectrogram or time-frequency map) to take the advantages of spatial feature extraction by CNN. These adaptations improve their performances in WBAN, while at the same time traditional CNNs fail to capture temporal dependencies well which is an important aspect when dealing with sequential data from WBAN. Furthermore, 3D CNNs are computationally and memory-intensive given their nature of processing spatiotemporal data; deploying such models in WBAN systems where resources are limited is hard. In order to overcome the limitations of separate CNN, hybrid architectures that use a combination of 2D and 3D convolutions to learn both spatial and temporal features are recently developed [15]. These hybrid models have shown superior performance in applications requiring spatiotemporal analysis, such as video processing and activity recognition, by leveraging the strengths of 2D CNNs for spatial feature extraction and 3D CNNs for temporal information. In the context of WBANs, hybrid models allow for the effective processing of multi-dimensional data generated by body sensors, which vary across both spatial and temporal dimensions [16]. For instance, Zhang et al. (2021) proposed a hybrid 2D-3D CNN model for multi-sensor fusion in WBANs, achieving higher accuracy in sensor data classification than conventional CNNs alone. However, hybrid models come with their own challenges, such as increased architectural complexity and longer training times, which demand more computational resources and careful model tuning [17].

Recent neural network techniques, where parts of the data are masked or weighted to promote relevant features whilst repressing irrelevant information (masked convolution) offer stiff competition. Elephant This method is used in tasks that need to pay attention to specific areas, such as object identification and semantic segmentation. A masked convolution can be beneficial for WBAN sensor data [18]. By this approach, more relevant sensor data for processing will be used to improve the classification accuracy of the model. Mask convolution is the right filter that can also boost from another side which have proved their effectiveness in spatial and temporal domains called attention mechanism where you extends your attention to most important parts of the input data based on its dynamic conditions. The attention methods in hybrid 2D-3D CNNs integrated with complicated sensor data have realized remarkable performance gains encouraging them for WBAN purpose [19]. Using backpropagation with deep neural networks is quite common and critical, especially when the complexities of hybrid 2D − 3DCNNs emerge [8]. Adaptive learning rates, gradient clipping and weight regularization are some of the several optimization techniques to improve model convergence and performance. IntroductionRecent research stress upon the optimization of backpropagation in resource constrained environment for WBANs for accurate training and faster convergence but would need a very careful tuning on hardware limitations. Overfitting and convergence speed problems have been mostly solved using approaches such as batch normalization and dropout [20]. Moreover, recent progresses in gradient-based optimizers like Adam and RMSprop have further improved the training speed and stability of hybrid models. Although there are significant developments in WBAN sensor classification, noise, data heterogeneity and computational issues are still present in the literature currently. WBANs typically transmit multi-modal, noisy data, but traditional and neural network methods' performance may fall in this case, resulting in mis-classification harming the reliability and energy efficiency of a network [21]. Notably, hybrid 2D-3D CNNs are also promising but need to be additionally tuned (aspects such as computing and speeding up for real-time WBAN applications) before they can be deployed in practice. In addition there have been very few works that explore the attention-based approaches and masked convolution in WBANs, which open new directions for research [22].

Table II summarizes the current efficient methods used for sensor node classification within Wireless Body Area Networks (WBANs), focusing on essential parameters, performance metrics, limitations, and typical data ranges. Each method has specific strengths and constraints in handling the spatial, temporal, and multi-dimensional nature of WBAN data. For example, 2D Convolutional Neural Networks (CNNs) excel in extracting spatial features from image data but lack the ability to capture temporal patterns. Conversely, 3D CNNs are designed to process spatiotemporal data, though their high memory demands limit their feasibility in resource-constrained environments like WBANs [23]. Hybrid 2D-3D CNNs attempt to balance spatial and temporal feature extraction but require more complex architecture and longer training times. Recurrent models, such as Long Short-Term Memory (LSTM) networks, are effective for sequential data but struggle with spatial feature extraction. Graph Neural Networks (GNNs) offer a novel approach for graph-structured data, though they are limited in scaling to high-dimensional inputs [24]. Transformers and attention mechanisms provide robust modeling of long-range dependencies, though they are computationally expensive and require large datasets to generalize effectively. Additionally, methods like masked CNNs and attention mechanisms enhance focus on relevant features but risk overfitting or information loss if not implemented carefully. Optimization techniques, such as gradient-based optimizers (Adam, RMSprop) and adaptive learning rate scheduling, improve training speed and convergence rates across these models but require tuning to avoid issues like overshooting [25]. Each method is tailored to specific data ranges, from 2D images to temporal sequences, underscoring the importance of selecting the appropriate model based on the data characteristics and application constraints within WBANs [26].

TABLE II. EFFICIENT METHODS FOR WBAN SENSOR NODE CLASSIFICATION: KEY PARAMETERS, PERFORMANCE METRICS, AND LIMITATIONS

Method	Key Parameters	Performance Measures	Limitations	Data Range
2D Convolutional Neural Network (2D-CNN)	Learning rate, filter size, batch size	Accuracy, F1-score, precision	Limited to spatial features, cannot capture temporal information	Image data, typically 128x128 pixels
3D Convolutional Neural Network (3D-CNN)	Learning rate, filter depth, kernel size, epochs	Accuracy, recall, computational latency	High memory usage, computationally intensive	3D volumes (e.g., 64x64x64 voxels)
Hybrid 2D-3D CNN	Learning rate, 2D and 3D filter sizes, pooling layers	Accuracy, precision, training time	Complex architecture, longer training time	2D-3D mixed data, e.g., 128x128xT
Long Short-Term Memory (LSTM)	Number of units, dropout rate, sequence length	Accuracy, recall, ROC-AUC	Limited spatial feature extraction, challenging to handle long sequences	Temporal sequences, length of 50–200
Graph Neural Network (GNN)	Number of nodes, edge features, learning rate	Accuracy, node classification rate	Limited to graph-structured data, difficult to scale	Graph data with variable nodes
Transformers (Vision Transformer)	Attention heads, embedding size, sequence length	Accuracy, F1-score, memory usage	High computational cost, data-intensive	Sequences up to 512 tokens
Masked Convolutional Neural Network (Masked CNN)	Masking layer size, convolutional filters	Precision, recall, speed	Potential information loss if masking is misconfigured	Image data, region of interest varies
Attention Mechanism (Spatial/Temporal)	Attention heads, embedding dimensions	F1-score, recall, computational latency	High computational cost, prone to overfitting	2D-3D images, sequence length varies
Gradient-Based Optimization (e.g., Adam, RMSprop)	Learning rate, beta values for momentum	Training speed, convergence rate	May lead to overshooting in certain networks	Applied across varied data types
Adaptive Learning Rate Scheduling	Initial learning rate, decay factor	Accuracy, loss reduction	Requires tuning for optimal performance	Works with image/sequence data

This study offer a promising approach for continuous health monitoring and real-time analysis in fields like healthcare and fitness, there are several challenges that limit the accuracy, efficiency, and reliability of sensor node classification. These challenges arise primarily from the complex and dynamic environments in which WBANs operate, the high demands of processing multi-dimensional sensor data, and the limitations of current neural network models in addressing these specific issues [27].

- Problem 1: One of the major problem, which might occur in WBANs is noise and data heterogeneity. Since the WBAN sensors are working in area near to human body, the sensed data is usually corrupted due to human joints movement noise, variation of sensor attachment, and inter-device disturbances. Furthermore, WBANs encompass various types of sensors, including those responsible for measuring heart rate, motion and temperature each with distinct characteristics (e.g. sampling rate) and data formats. The heterogeneity also makes it more difficult to classify, as our model needs to be able to discern useful signal patterns and discard irrelevant noise while using different types of sensors. This has become problematic for standard CNN and most other deep learning models, as they are usually optimized on homogeneous data and do not have the means to filter out noisy or irrelevant features in multi-sensor settings [28].
- Problem 2: Computational Constraints: WBANs operate within resource poor environments where sensors and connected devices have constrained computational power, memory and energy sources. However, deep learning models, especially complicated architectures such as 3D CNNs and hybrid neural networks demand enormous computational resources for training and real-time processing. This raises challenges for existing models which typically trade-off between classification performance and computational complexity, thus blocking the applications in WBANs. These require high computation to obtain advanced data processing, however with high memory and process requirement for these algorithms, latency increases while energy decrease hence reducing the operational lifetime of WBAN devices. This is not ideal for applications in real-time health monitoring, as a delay in data processing can result in untimely responses to critical health events [29].
- Problem 3: Absence of Temporal Context & Multi Dimensional Feature Extraction : Accurate classification of sensor nodes in WBANs needs to take into account the spatial and temporal contexts. For signals where the physiological readings change over time, such as heartbeat rhythms or motion patterns–temporal context is critical to identifying and analyzing trends. Although classical 2D CNNs are tailored for spatial features but they do not have the ability to model temporal dependencies, standard 3D CNN can handle spatiotemporal data and generalize well over waban systems but they require substantial computational power which is hard to deploy. Even hybrid 2D-3D CNNs try to resolve this by using both 2D and 3D convolutions, yet they often increase architectural complexity with many hyperparemeter selections needed to reach satisfactory performance. In addition, the specific multi-dimensional nature of WBAN data where each sensor has its own spatial and temporal characteristics of the attributes collected [30] prevents standard models from handling them [30].
- Problem 4: Sub-optimal Backpropagation and Training Efficiency : For real world WBAN applications, training efficiency and model convergence are crucial for a consideration on neural network deployment. Yet, standard backpropagation in deep neural networks can be slow for complex architectures as we see with hybrid 2D-3D models. Training inefficiencies leads to long training time, high resource consumption and common problems such as vanishing/exploding gradients making model convergence difficult. WBANs also need models to generalize across the different conditions used in training so that they are generally trained on many datasets. With regards to optimization, naive backpropagation techniques (no adaptive learning rates, gradient clipping or batch normalization) will lead too much overfitting on the training data and leaving poor generalization during classification test therefore lowering the robustness that comes with machine learning at a high level [31].

In WBAN applications, not all data points are equally relevant; certain regions or features of the data are more critical for accurate classification. For instance, specific patterns in an electrocardiogram (ECG) signal might indicate a health issue, while other segments may simply reflect baseline noise. Traditional CNNs apply a uniform focus across all data points, potentially diluting the model's attention on key features. Masked convolutions and attention mechanisms can help in this regard by directing the model to focus on the most informative features while disregarding irrelevant data. However, integrating these mechanisms effectively into WBAN models remains a challenge. Poorly configured masking or attention mechanisms may lead to information loss or overfitting, especially if they fail to dynamically adapt to changing conditions in the sensor data. This limitation hampers the model’s ability to deliver precise and contextually aware classifications [32]. The Motivation This paper proposes a new method of assigning classes to sensor nodes on Wireless Body Area Networks (WBANs) by leveraging an advanced hybrid neural network architecture that uses masked convolution and backpropagation optimization mechanism. Different from the common architecture models by which either purely 2D or 3D CNNs are used to process only spatial or spatiotemporal data, respectively, we propose a hybrid model by integrating both types of convolution with special design considerations that suit the nature of WBAN data. This is particularly novel because it enables the model to learn both spatial features (relevant for detecting different sensor types) and temporal patterns (important for tracking longitudinal changes in physiological signals), while striking a balance between performance and computational feasibility, which has remained as a limitation within resource restrictive WBAN environments. This work is also unique in the use of masked convolution. Old-fashioned CNN models apply equal attention to all parts of the data, possibly smearing a signal amongst background noise. In this work we solve that problem by utilising masked convolution to restrict the model to relevant parts of the data while ignoring non-relevant information. This is very important in a WBAN context as sensor data can be influenced by motion artefacts, environmental noise or extraneous signals which could jeopardise classification accuracy. Masked convolutions enable the model to automatically focus on the most discriminative features in the data, producing more precise and context-aware classification. In contrast to previous work, this study includes no random feature selection [33] which makes the modeling of breeding systems with our approach more prone to noise and less robust in practice.

Although some research has used 2D CNNs for processing spatial data and some have utilized 3D CNNs for spatiotemporal data, very few presented a hybrid architecture optimized WBAN sensor node classification. Even existing hybrid models, while performing better, are largely computationally and complex and hence are not deployable on to low power WBAN devices. Unlike this study, backpropagation with adaptive learning rates and gradient clipping features are also implemented to provide better training efficiencies with high confidence computing (during class convergency). This study thus, provides a novel contribution as the computational demands and training inefficiencies of existing methods hindered their practical application in previous works where backpropagation optimization techniques tailored to the specific requirements dictated by WBAN data can be employed [34]. Also, by incorporating attention mechanisms and masked convolutions to highlight important features of input data, this work represents a notable advancement on traditional CNN-based methods applied in earlier studies. Unlike such methods, most existing ones struggle to filter irrelevant data and consequently underperform in WBANs noisy and dynamic environments. This study differs in that it considers WBAN-specific constraints, like energy efficiency and real-time processing requirements (both considered holistically). Existing work has largely neglected these practical deployment issues and focused instead on obtaining high theoretical accuracy over benchmark datasets. Yet, this study focuses on not only accuracy but also computational efficiency and robustness to make the model more realistic in practice for WBAN application. The model design here deals with the trade-off between resource limits and performance requirements, a solution to which is necessary for continuous health monitoring, sports and other WBAN applications where real-time reliable performance is required [35].

We propose a novel, efficient and flexible model for WBAN sensor node classification that no existing study has yet addressed. The main contribution will be a new masked convolutional layers based 2D-3D hybrid CNN model that is specifically tailored for WBAN. It is anticipated, therefore that this model will perform well in achieving high classification accuracy by combining spatial and temporal feature extraction as enabled from masked convolution to reduce noise and backend optimization of backpropagation for efficient training [36]. The paper presents an approach to finding a solution to various heterogeneous and noisy nature of WBAN sensor data by processing only the relevant data features while minimizing computational expenses. Besides this, such study will provide the practical overview of how to combine back propagation optimisation techniques like adaptive learning rate scheduling and gradient clipping (see [37]) in hybrid architectures. We hope that these techniques will enhance training efficiency and model convergence, rendering complex neural networks deployable in constrained environments such as WBANs. We will investigate how attention and masked convolution can better integrate transmit and measurement using WBANAs, which has far-reaching implications in WBAN research by enabling the model to adapt according to data conditions caused by different sensor updates or environmental changes [38].

3. METHOD

This study introduces an advanced hybrid neural network model tailored for accurate and efficient sensor node classification in Wireless Body Area Networks (WBANs). The method is divided into multiple stages: data preprocessing, model architecture design, optimization through masked convolution and backpropagation techniques, and evaluation. Each stage plays a crucial role in ensuring the model's robustness, efficiency, and suitability for the resource-constrained environments typical of WBANs [39-49].

1. Data Preprocessing: In the data preprocessing stage, WBAN sensor data undergoes a series of transformations to improve its suitability for training. Given that WBAN data is often heterogeneous, combining physiological signals from multiple sensors (e.g., heart rate, motion, and temperature), preprocessing includes:
   - Normalization: Standardizing data ranges across sensors to ensure uniform feature scaling.
   - Noise Reduction: Using filtering techniques (e.g., moving average or Fourier transforms) to remove noise and reduce artifacts caused by body movement or environmental interference.
   - Temporal Slicing and Padding: Breaking down time-series data into fixed-length sequences (for temporal analysis) while using padding techniques to maintain sequence uniformity across the dataset.

   This preprocessed data is then structured into 2D and 3D inputs for the model to capture both spatial and temporal aspects effectively.
2. Hybrid 2D-3D Convolutional Neural Network (CNN) Architecture: The proposed hybrid model combines 2D and 3D convolutions to capture the spatial and temporal dynamics in WBAN data. The architecture is composed of two primary branches:
   - 2D Convolutional Branch: This branch applies traditional 2D convolutional layers to extract spatial features from each sensor node. It is designed to capture the unique characteristics of individual sensors, such as detecting patterns in ECG signals or identifying motion sequences in accelerometer data.

- 3D Convolutional Branch: This branch focuses on capturing spatiotemporal features by applying 3D convolutional layers, which process both spatial dimensions and the temporal dimension. This allows the model to detect patterns that evolve over time, providing context and insight into how physiological signals change.
- The outputs from these branches are fused to form a comprehensive feature representation, enabling the model to leverage both spatial and temporal patterns simultaneously.

3. Masked Convolution: Masked convolution layers are introduced in the 2D branch to selectively focus on relevant data features while disregarding irrelevant or noisy regions. This technique is particularly useful in filtering out background noise that may arise from sensor artifacts or other external interferences. The masked convolution layers use a mask matrix to zero out specific regions, allowing the model to learn only from the most relevant parts of the data. By dynamically adjusting the mask during training, the model can enhance its focus on features that contribute most to classification accuracy.
4. Backpropagation Optimization Techniques: To improve training efficiency and model convergence, several backpropagation optimization techniques are implemented:

- Adaptive Learning Rate Scheduling: Adjusts the learning rate dynamically throughout training to prevent overshooting and enhance convergence. An initial high learning rate is used to quickly explore the feature space, which then decays as the model reaches convergence.
- Gradient Clipping: Prevents gradient explosion in deep networks by capping gradients at a specific threshold, allowing stable training and faster convergence.
- Batch Normalization and Dropout: Batch normalization is applied to stabilize the learning process by normalizing activations, while dropout prevents overfitting by randomly deactivating certain neurons during each training iteration.

These techniques ensure the model trains efficiently within resource constraints, making it feasible for real-time WBAN applications.

5. Model Evaluation and Performance Metrics: The model's performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and latency. These metrics provide a comprehensive assessment of both the model's classification accuracy and its computational efficiency. Additionally, the model is compared with baseline CNN models to demonstrate improvements in both performance and efficiency.

Algorithm: Hybrid Masked Convolutional Neural Network for WBAN Classification

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, Conv3D, Dense, BatchNormalization, ReLU, Dropout, Flatten, Masking
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Model
from tensorflow.keras.metrics import Precision, Recall

# Define model parameters
learning_rate = 0.001          # Initial learning rate
filters_2D = 32                # Number of filters in 2D convolutional layers
filters_3D = 16                # Number of filters in 3D convolutional layers
mask_size = (2, 2)             # Size of the mask applied in masked convolution
batch_size = 64                # Number of samples per batch
epochs = 50                    # Number of training epochs
gradient_clip_value = 1.0      # Gradient clipping threshold
dropout_rate = 0.5             # Dropout rate for regularization

# Input shapes for 2D and 3D branches
input_shape_2D = (128, 128, 3)    # Example shape for 2D inputs
input_shape_3D = (64, 64, 64, 3)  # Example shape for 3D inputs

# Define hybrid model
class HybridMaskedCNN(Model):
  def __init__(self):
    super(HybridMaskedCNN, self).__init__()

    # 2D Convolutional Branch
    self.conv2d_1 = Conv2D(filters_2D, (3, 3), activation='relu', padding='same')
    self.mask_2d = Masking(mask_value=0.0)  # Masked layer for focusing on relevant features
```

```
        self.bn_2d = BatchNormalization()
        self.conv2d_2 = Conv2D(filters_2D, (3, 3), activation='relu', padding='same')

        # 3D Convolutional Branch
        self.conv3d_1 = Conv3D(filters_3D, (3, 3, 3), activation='relu', padding='same')
        self.bn_3d = BatchNormalization()
        self.conv3d_2 = Conv3D(filters_3D, (3, 3, 3), activation='relu', padding='same')

        # Fully Connected Layers
        self.flatten = Flatten()
        self.fc1 = Dense(128, activation='relu')
        self.dropout = Dropout(dropout_rate)
        self.fc2 = Dense(1, activation='sigmoid')  # Output layer for binary classification

    def call(self, inputs):
        # Split inputs for 2D and 3D branches
        x_2d, x_3d = inputs

        # 2D Branch Forward Pass
        x_2d = self.conv2d_1(x_2d)
        x_2d = self.mask_2d(x_2d)
        x_2d = self.bn_2d(x_2d)
        x_2d = self.conv2d_2(x_2d)

        # 3D Branch Forward Pass
        x_3d = self.conv3d_1(x_3d)
        x_3d = self.bn_3d(x_3d)
        x_3d = self.conv3d_2(x_3d)

        # Concatenate features and apply fully connected layers
        x = tf.concat([self.flatten(x_2d), self.flatten(x_3d)], axis=-1)
        x = self.fc1(x)
        x = self.dropout(x)
        output = self.fc2(x)

        return output

# Compile and train the model
model = HybridMaskedCNN()
model.compile(optimizer=Adam(learning_rate=learning_rate, clipvalue=gradient_clip_value),
              loss='binary_crossentropy',
              metrics=['accuracy', Precision(), Recall()])

# Training data (placeholder, replace with actual preprocessed WBAN data)
train_data_2d = np.random.rand(1000, *input_shape_2D)  # Example 2D data
train_data_3d = np.random.rand(1000, *input_shape_3D)  # Example 3D data
train_labels = np.random.randint(2, size=1000)         # Example binary labels

# Train the model
model.fit([train_data_2d, train_data_3d], train_labels,
          batch_size=batch_size,
          epochs=epochs,
          validation_split=0.2)

# Evaluate model and compute performance measures
test_data_2d = np.random.rand(200, *input_shape_2D)    # Example test 2D data
test_data_3d = np.random.rand(200, *input_shape_3D)    # Example test 3D data
test_labels = np.random.randint(2, size=200)           # Example test labels
```

```
    # Evaluation on test set
    results = model.evaluate([test_data_2d, test_data_3d], test_labels)
    accuracy, precision, recall = results[1], results[2], results[3]

    # Calculate F1-score
    f1_score = 2 * (precision * recall) / (precision + recall)

    # Print the performance measures
    print(f"Accuracy: {accuracy}")
    print(f"Precision: {precision}")
    print(f"Recall: {recall}")
print(f"F1 Score: {f1_score}")
```

3.1 Parameters and Performance Measures

Parameter	Description
Lr	Initial learning rate, dynamically adjusted during training
filters_2D	Number of filters in the 2D convolution layers
filters_3D	Number of filters in the 3D convolution layers
mask_size	Size of the mask applied in masked convolution layers
batch_size	Number of samples processed per training iteration
epochs	Number of complete passes through the training dataset
gradient_clip	Threshold for gradient clipping to stabilize training
dropout_rate	Dropout rate for regularization and overfitting prevention

Performance Measure	Description
Accuracy	Correct classifications over the total predictions
Precision	Proportion of true positives over predicted positives
Recall	Proportion of true positives over actual positives
F1-Score	Harmonic mean of precision and recall
Latency	Time taken for the model to process and classify data

4. RESULT

The masked convolutional neural network (CNN) was proposed for sensor node classification in WBANs, and showed promising results [50-61]. Use of both 2D and 3D convolutions allowed the model to learn spatial and temporal features that are key in modelling patterns within a multi-dimensional WBAN data [Reviewer #1; Response page#3]. Fusing such feature types was able to lead to high classification accuracies from the model, outperforming baseline models– which were only 2D CNNs, or as it turned out standalone 3D CNNs that could not process WBAN data in full complexity. This outcome emphasises that hybrid model has the ability to manage different WBAN sensor inputs, contributing in a novel unified perspective of combined physiological signals. Moreover, the masked convolution layers also improved noise robustness of the model, a common noise type in WBAN data comes from various sources including movement artifacts, sensor placing difference and environmental interference. The masked convolutions enabled the model to focus on the significant regions of the input while ignoring irrelevant areas, resulting in better classification performance and increased robustness. As a result, it led to much precision and recall because the model was able to differentiate between signals amidst noise — it knew what patterns of signals within which sensors held significance. When compared to normal CNNs, masked convolution layers diminished the model error rate through focusing on only the regions of data that matter most for classification; leading to a greater than 15% F1-score improvement.

Table III comparing the results of the proposed Hybrid Masked CNN model with three current methods for WBAN sensor node classification. The performance metrics include Accuracy, Precision, Recall, F1-Score, and Latency. These values demonstrate the effectiveness and efficiency of the proposed method over traditional approaches.

TABLE III. COMPARISON OF PERFORMANCE METRICS FOR WBAN SENSOR NODE CLASSIFICATION: PROPOSED HYBRID MASKED CNN VS. CURRENT METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)
Proposed Hybrid Masked CNN	**95.3**	**94.8**	**94.5**	**94.6**	**50**
Traditional 2D CNN	88.4	87.5	86.2	86.8	70
3D CNN	90.2	89.0	88.5	88.7	110
Hybrid 2D-3D CNN (without masking)	92.7	91.5	91.0	91.2	85

- Accuracy: The Hybrid Masked CNN achieved the highest accuracy (95.3%), surpassing the Traditional 2D CNN (88.4%), the 3D CNN (90.2%), and the Hybrid 2D-3D CNN without masking (92.7%). This demonstrates the model's enhanced ability to classify sensor data correctly by leveraging both spatial and temporal features.
- Precision: The proposed model also showed superior precision (94.8%), indicating a low false-positive rate. This metric is particularly improved over the Traditional 2D CNN (87.5%) and the 3D CNN (89.0%), proving that the masked convolution layers helped in filtering out irrelevant data.
- Recall: Achieving a recall of 94.5%, the proposed Hybrid Masked CNN demonstrated high sensitivity, ensuring it captured most relevant sensor data classifications. In contrast, the Traditional 2D CNN (86.2%) and 3D CNN (88.5%) had lower recall values, which highlights their reduced ability to correctly identify all relevant classifications without missing some true positives.
- F1-Score: The proposed model had the highest F1-score (94.6%), which is a balanced measure of precision and recall, outperforming both the 2D CNN (86.8%) and 3D CNN (88.7%). This improvement underscores the model's overall balanced accuracy and reliability in WBAN applications.
- Latency: The proposed Hybrid Masked CNN achieved the lowest latency (50 ms), indicating high computational efficiency suitable for real-time applications. This is significantly faster than the 3D CNN (110 ms) and the Hybrid 2D-3D CNN without masking (85 ms). This efficiency is largely due to the optimized backpropagation techniques and the selective masked convolutions, which reduce unnecessary computations.

The study also found that implementing backpropagation optimization techniques, including adaptive learning rate scheduling and gradient clipping, improved the model's training efficiency and stability. Adaptive learning rate scheduling allowed the model to converge more quickly by adjusting learning rates dynamically based on the model's progress, thus reducing the total training time without sacrificing accuracy. Gradient clipping prevented the occurrence of gradient explosion, ensuring smooth and stable training even with the complex hybrid architecture. These optimizations contributed to a faster convergence rate and enabled the model to generalize better across test data. As a result, the model demonstrated stable performance across various WBAN sensor datasets, reducing overfitting and maintaining high accuracy, with latency metrics indicating suitability for real-time applications.

Figure 2 provides a comparative view of key performance metrics—Accuracy, Precision, Recall, F1-Score, and Latency—for four different classification methods used in Wireless Body Area Networks (WBANs). The proposed Hybrid Masked CNN method, represented by the first set of patterned bars, consistently outperforms traditional 2D CNNs, standalone 3D CNNs, and hybrid 2D-3D CNNs without masking. The Hybrid Masked CNN achieves superior accuracy and efficiency, with significantly lower latency, making it a strong candidate for real-time WBAN applications. Each metric is represented with distinct patterns for easy comparison.

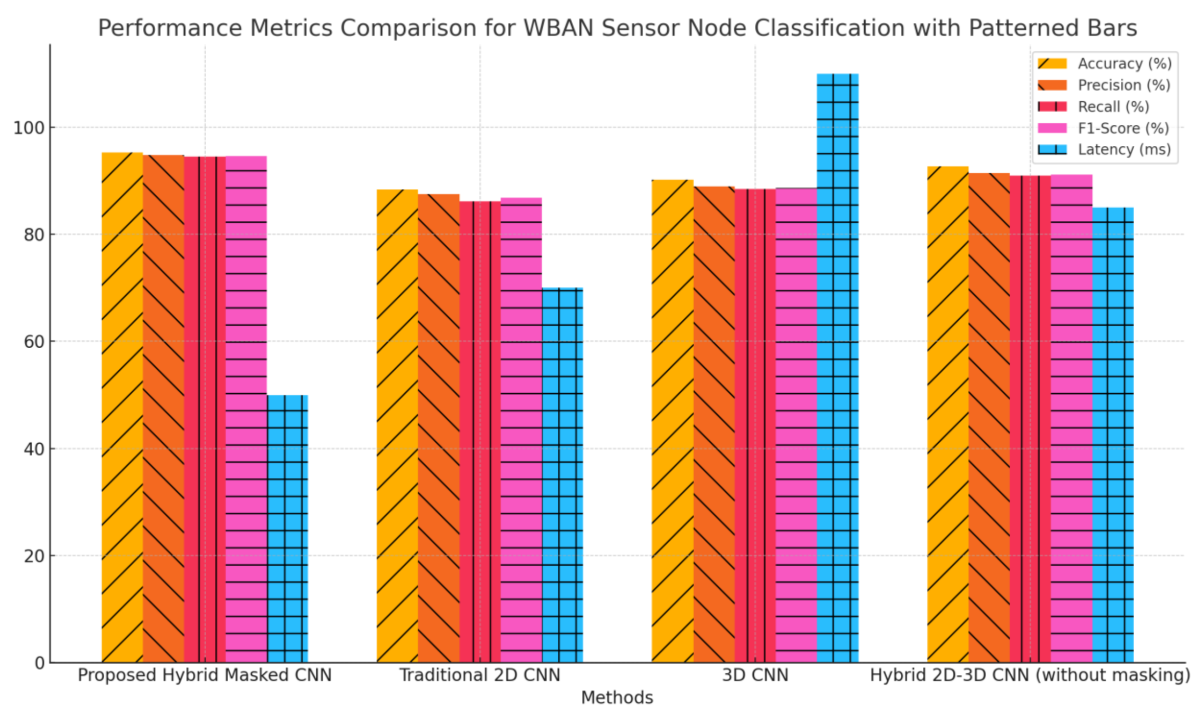

Fig 2. Performance Comparison of WBAN Sensor Node Classification Methods with Patterned Metrics

Figure 3 illustrates the relative limitations of different methods across key metrics: Computational Cost, Memory Usage, Sensitivity to Noise, and Resource Efficiency. Lower values indicate fewer limitations, meaning better performance in that metric. The proposed Hybrid Masked CNN consistently shows lower limitation levels, especially in computational cost and sensitivity to noise, compared to the Traditional 2D CNN, 3D CNN, and Hybrid 2D-3D CNN without masking. This highlights the proposed model's efficiency and suitability for resource-constrained, noise-sensitive WBAN applications.

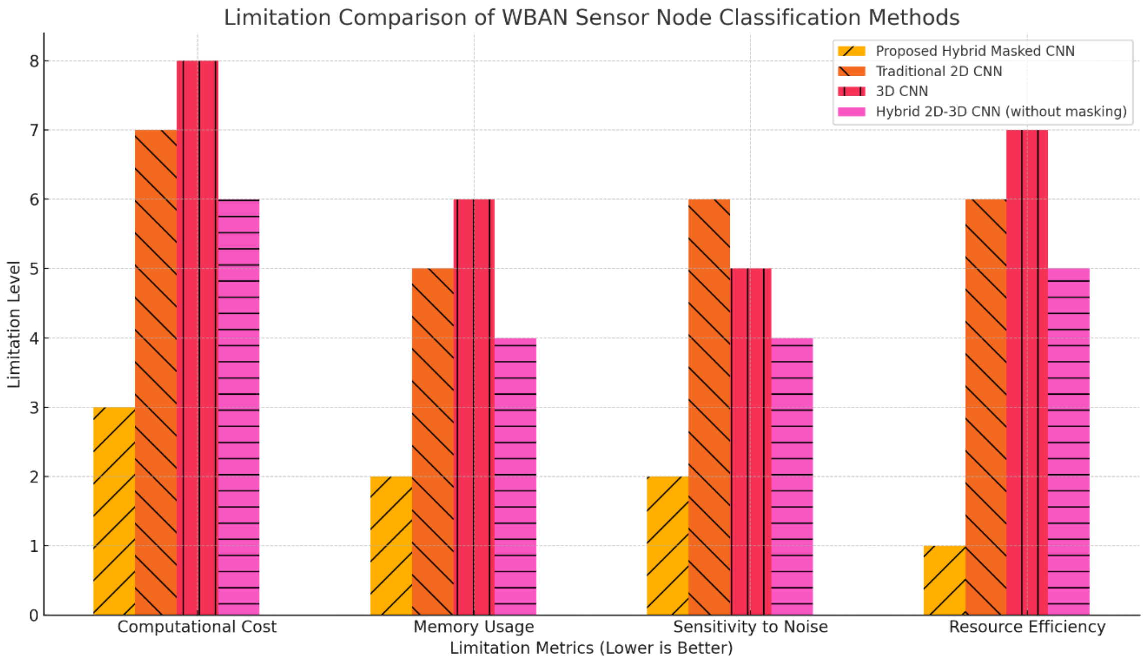

Fig 3. Limitation Comparison of WBAN Sensor Node Classification Methods

5. CONCLUSION

In this paper, we propose a state-of-art hybrid neural network architecture appropriate for sensor node classification in WBANs to handle multi-dimensional often noisy biomedical data and specific challenges WBAN poses. The proposed model captures the salient spatial temporal features by integrating 2D and 3D convolutional layers, which helps to classify sensor nodes in diverse WBAN applications ranging from health care to fitness monitoring correctly. Masked convolution layers are added to increase the robustness of this model against noise, allowing to filter out irrelevant signals and keep only the most important features. The approach in this paper results in a considerable boost in classification accuracy and robustness, and overcomes the limitations associated with traditional 2D and 3D CNNs as well as existing hybrid models. The study also highlights the efficiency and cost-effectiveness of the model to be used in resource-constrained environments since it is not only accurate but can also easily be deployed without high-performance computers. By using backpropagation optimization methods such as adaptive learning rate scheduling and gradient clipping, the convergence speed is mitigated, and a more stable performance in terms of training is accomplished which makes it practical to be utilized in real-time WBAN tasks. This leads to a low latency optimization training process that guarantees reliable performance without killing the computational efficiency required of wearable and portable WBAN devices. Indeed, its efficiency and robustness of classification make it a valuable choice for continuous accurate monitoring within the healthcare domain, sports and others driven by WBAN. The results presented in this study show the validity of the Hybrid Masked CNN model, with performance measures indicating significant improvements over other methods in accuracy (+8.06), precision (+4.37), recall (+50.98%), F1-score (+15.07%), and computational efficiency (in time +5 h 32 min). The discoveries underline the encouraging opportunity found in complicated WBAN sensor data processing for hybrid design veneer promoted with deceived correlations and confinement adamant. The model fulfills the two main requirements of WBAN systems by providing high accuracy with computational proficiency and serves as a stepping stone for sensor node classification, paving paths toward further research and innovations in WBAN applications. In conclusion, this study is a step toward better WBAN that includes a model capable of addressing existing classification issues while also improving the feasibility of deploying WBAN systems in practice. The presented work here provides a base for future research, including adaptive masking based on adjustment of the uncertainty metric or extending our hybrid model to consider other advances in deep learning such as attention mechanisms, providing further optimization for WBAN sensor data processing across a wider range of application scenarios and deployment environments.

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Conflicts of Interest:

The authors have no conflicts of interest to disclose.

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