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A Comparative Deep Learning Architecture for Bipolar Disorder Prediction Using Symptom-Based Clinical Data

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Abstract:

Bipolar disorder is a chronic and debilitating psychiatric illness characterized by recurrent episodes of mania and depression, significantly affecting an individual's emotional stability, cognitive functioning, and quality of life. Accurate diagnosis remains challenging due to symptom overlap with other mood disorders and reliance on subjective clinical assessments. This study presents a clinically driven deep learning framework for the automated prediction of bipolar disorder using a structured, symptom-based dataset reflecting common psychiatric indicators. Three deep learning models—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—were designed and evaluated to analyze behavioral and clinical symptom patterns. Standard preprocessing techniques, including normalization and train–test splitting, were applied to ensure reliable model performance. The predictive capability of each model was assessed using classification accuracy and confusion matrix analysis. Results demonstrate that deep learning approaches effectively model complex clinical relationships within psychiatric data. The ANN model achieved the highest predictive accuracy, indicating its suitability for tabular clinical datasets. This work emphasizes the potential of deep learning as a supportive clinical decision-making tool for early bipolar disorder screening and improved mental health assessment.

Keywords: Artificial Intelligence, Deep learning, Psychiatric Illness, Bipolar Disorder, Mental health.

I. INTRODUCTION:

Bipolar disorder is a chronic and recurrent mood disorder characterized by alternating episodes of mania, hypomania, and depression, leading to significant impairments in emotional regulation, cognition, and social functioning. It affects millions of individuals worldwide and is recognized as one of the leading causes of disability among psychiatric illnesses [1]. Despite its prevalence, bipolar disorder remains underdiagnosed or misdiagnosed, particularly during early stages, due to symptom overlap with major depressive disorder and reliance on subjective clinical judgment [2]. Delayed or incorrect diagnosis often results in inappropriate treatment, increased relapse rates, and elevated risk of suicide, highlighting the need for reliable and objective diagnostic support systems.

Traditional diagnostic approaches for bipolar disorder are largely based on structured clinical interviews, patient self-reports, and standardized rating scales such as the Young Mania Rating Scale (YMRS) and mood disorder questionnaires [3]. While clinically effective, these methods depend heavily on patient recall, clinician expertise, and longitudinal observation, which can introduce bias and variability. Moreover, the episodic nature of bipolar disorder complicates continuous monitoring, making early detection and intervention particularly challenging. As a result, there is growing interest in computational approaches that can assist clinicians by analyzing symptom patterns in a consistent and data-driven manner.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have demonstrated considerable potential in healthcare applications, particularly in disease prediction and decision support systems [4]. In mental health research, ML techniques have been applied to detect depression, anxiety, schizophrenia, postpartum depression and mood disorders using clinical, behavioral, and digital data sources [5]. However, conventional ML algorithms often require extensive feature engineering and may struggle to capture the complex, non-linear relationships inherent in psychiatric symptom data. This limitation has motivated the adoption of deep learning (DL) techniques, which can automatically learn hierarchical feature representations from raw or structured inputs.

Deep learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have shown promising performance in modeling complex biomedical and temporal data [6]. ANN architectures are well suited for structured, tabular clinical datasets due to their ability to model non-linear relationships between features. CNNs, although originally developed for image processing, have been successfully adapted for one-dimensional clinical and signal data, enabling efficient local pattern extraction [7]. LSTM networks, a specialized form of recurrent neural networks, are designed to capture long-term dependencies and have been widely used in time-series health data analysis [8]. These models collectively provide a robust framework for exploring predictive patterns in psychiatric symptom datasets.

In the context of bipolar disorder, deep learning–based predictive systems can serve as valuable clinical decision-support tools by identifying high-risk individuals and assisting in early screening. However, the availability of open-access, patient-level bipolar disorder datasets remains limited due to ethical, privacy, and regulatory constraints. To address this challenge, clinically inspired datasets have been increasingly used in academic research to evaluate computational models while preserving patient confidentiality [9].

Motivated by these considerations, this study presents a deep learning–based approach for bipolar disorder prediction using a symptom-level dataset reflecting commonly observed psychiatric indicators. Three deep learning models—ANN, CNN, and LSTM—are implemented and comparatively analyzed to evaluate their effectiveness in modeling bipolar disorder symptoms. The dataset is preprocessed using standard normalization techniques and partitioned into training and testing subsets to ensure unbiased evaluation. Model performance is assessed through accuracy metrics and confusion matrix analysis, enabling a systematic comparison of predictive capability. By integrating deep learning techniques with clinically relevant features, this work aims to contribute toward the development of intelligent and data-driven mental health assessment systems that support early bipolar disorder screening.

II.LITERATURE REVIEW:

Bipolar disorder is a complex mood disorder that presents significant diagnostic challenges due to fluctuating emotional states and overlapping symptoms with other psychiatric conditions. Conventional diagnosis primarily relies on longitudinal clinical observation and structured interviews, which can delay identification and treatment initiation. These limitations have encouraged researchers to investigate computational techniques that can support clinicians by analyzing symptom patterns in a more consistent and objective manner [1].

Early research efforts in bipolar disorder prediction employed traditional machine learning algorithms using demographic and questionnaire-based features. Methods such as logistic regression, support vector machines, and decision trees demonstrated the feasibility of automated classification; however, their performance was often constrained by limited feature representation and an inability to effectively model non-linear relationships among psychiatric symptoms [2]. As mental health data became more complex, these limitations highlighted the need for more advanced learning techniques.

Deep learning has emerged as a powerful alternative due to its capacity to automatically learn hierarchical feature representations from data. Artificial Neural Networks (ANN) have been widely applied in healthcare analytics, particularly for structured clinical datasets. In psychiatric applications, ANN models have shown improved classification performance by capturing complex interactions between mood, behavioral, and cognitive features without extensive manual feature engineering [3]. This makes ANN architectures particularly suitable for symptom-based bipolar disorder datasets.

Convolutional Neural Networks (CNN) have also been explored beyond their original use in image processing. By treating clinical features as one-dimensional inputs, CNN models are capable of identifying localized patterns and correlations within symptom data. Several studies in mental health analytics have reported that CNN-based models outperform conventional classifiers by effectively extracting discriminative feature representations from clinical and behavioral measurements [4]. These characteristics make CNNs a viable option for bipolar disorder prediction when symptom relationships are considered.

Long Short-Term Memory (LSTM) networks are designed to capture temporal dependencies and have been extensively used in healthcare applications involving sequential data. In bipolar disorder research, LSTM models have been applied to mood tracking, activity monitoring, and longitudinal symptom assessment, enabling the modeling of mood variability over time [5]. Such models are particularly relevant for bipolar disorder, where symptom progression and relapse patterns are inherently temporal. Even when applied to structured data, LSTM architectures provide insights into dependency relationships among features.

A persistent challenge in bipolar disorder research is the limited availability of open-access patient-level datasets due to privacy and ethical concerns. To overcome this barrier, researchers increasingly employ synthetic or clinically inspired datasets generated using established psychiatric symptom criteria. These datasets allow for controlled experimentation and model comparison while maintaining data privacy [6]. When carefully designed, synthetic datasets have been shown to support meaningful evaluation of predictive models in mental health research.

In summary, existing studies demonstrate the growing role of deep learning techniques in bipolar disorder prediction. However, direct comparisons among multiple deep learning architectures using symptom-based datasets remain limited. This study addresses this gap by implementing and evaluating ANN, CNN, and LSTM models within a unified framework, providing a comparative analysis of their effectiveness for bipolar disorder prediction.

III. METHODOLOGY

The primary objective of this study is to develop a deep learning framework capable of accurately predicting bipolar disorder using a structured, symptom-level dataset. The methodology is organized into four main stages: dataset preparation, preprocessing, model development, and performance evaluation. Each stage is designed to ensure robust model learning, reproducibility, and interpretability.

A. Dataset Preparation

Due to the limited availability of public patient-level bipolar disorder data caused by privacy and ethical restrictions, a clinically inspired synthetic dataset was created. The dataset includes 500 samples, each consisting of key symptom features commonly used in psychiatric assessments, including mood swings, manic and depressive episode scores, sleep disturbance, energy level, concentration difficulty, impulsivity, and anxiety level. The target variable, bipolar_label, is binary, indicating whether the subject exhibits bipolar disorder (1) or is a healthy control (0) [1], [2]. Synthetic data generation was guided by established psychiatric criteria to ensure clinical relevance and simulate realistic symptom distributions [3].

B. Data Preprocessing

Prior to model training, the dataset underwent several preprocessing steps to optimize learning. Numerical features were normalized using standard scaling, transforming each feature to have a mean of zero and unit variance. This step reduces feature dominance and ensures convergence stability during neural network training [4]. The dataset was subsequently partitioned into training (80%) and testing (20%) subsets using stratified sampling to maintain proportional class distribution and prevent sampling bias. For models that require sequential input, such as LSTM and CNN, the features were reshaped into a three-dimensional format (samples × features × 1) to enable compatibility with convolutional and recurrent architectures [5].

C. Deep Learning Model Development

Three deep learning architectures were developed for comparative analysis: ANN, CNN, and LSTM.

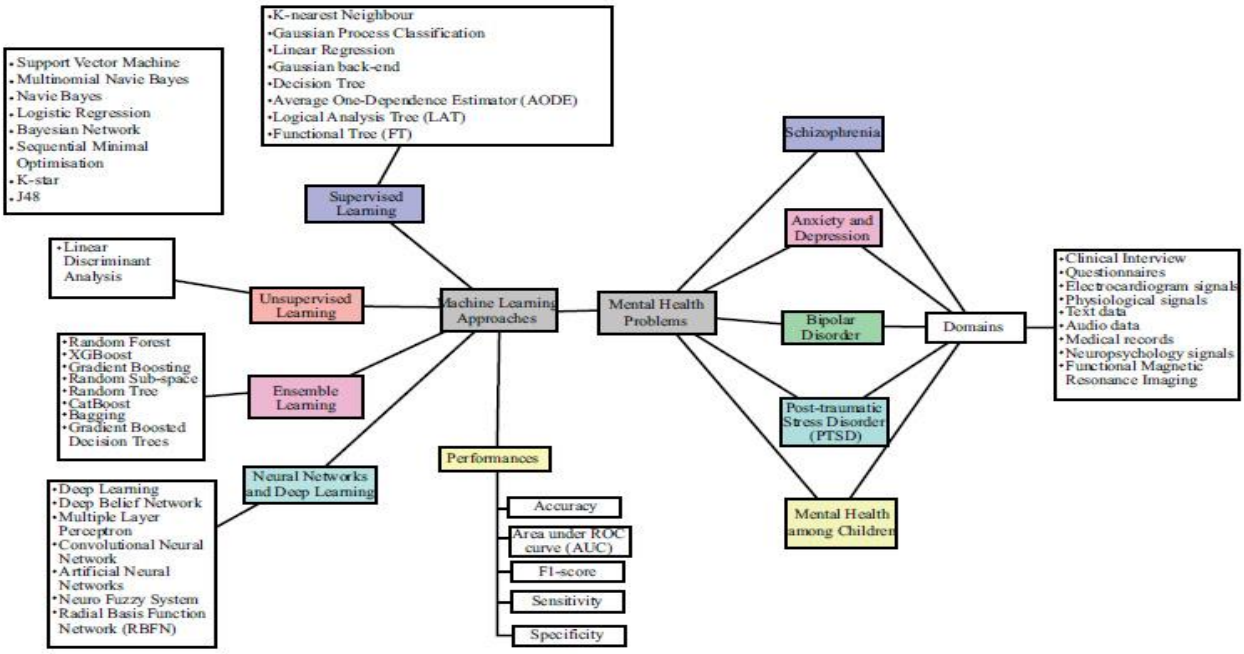


Figure:3.1 - *Comprehensive framework for exploring deep learning approaches in bipolar disorder prediction*

1. **Artificial Neural Network (ANN):**

   The ANN model consists of a fully connected feedforward network with two hidden layers comprising 64 and 32 neurons, respective ReLU activation functions were applied in hidden layers to introduce non-linearity, while a sigmoid activation function was used in the output layer for binary classification. The network was trained using the **Adam optimizer** with binary cross-entropy as the loss function [6].

2. **Convolutional Neural Network (CNN):**

   The CNN model was adapted to one-dimensional clinical data by treating the features as sequential signals. The architecture includes a convolutional layer with 32 filters and kernel size of 2, followed by a max-pooling layer and a fully connected layer of 32 neurons. ReLU activations were applied in hidden layers, and a sigmoid function was used for output. This design enables the CNN to capture local feature patterns and interactions among symptoms [7].

3. **Long Short-Term Memory (LSTM):**

   The LSTM model incorporates a single LSTM layer with 32 units, capable of capturing temporal dependencies in feature sequences. Although the dataset is static, LSTM was applied to leverage its ability to model sequential correlations, which may represent latent temporal patterns among symptom interactions. The LSTM output is connected to a fully connected layer with a sigmoid activation for classification [8].

All models were trained for 30 epochs with a batch size of 16. A validation split of 10% was used during training to monitor overfitting and optimize hyperparameters.

D. Performance Evaluation

The predictive performance of each model was assessed using several metrics. Classification accuracy was calculated to measure overall correctness, while confusion matrices were analyzed to quantify true positive, false positive, true negative, and false negative rates. Additionally, precision, recall, and F1-score metrics were computed to provide a balanced evaluation of the models' ability to correctly identify bipolar disorder cases [9]. Visualizations of model performance, including accuracy plots over epochs and comparative bar charts, were generated to facilitate interpretation and comparative analysis.

By systematically implementing and evaluating ANN, CNN, and LSTM architectures on the clinically inspired symptom dataset, this methodology provides a comprehensive framework for exploring deep learning approaches in bipolar disorder prediction, which is present in Figure: 3.1

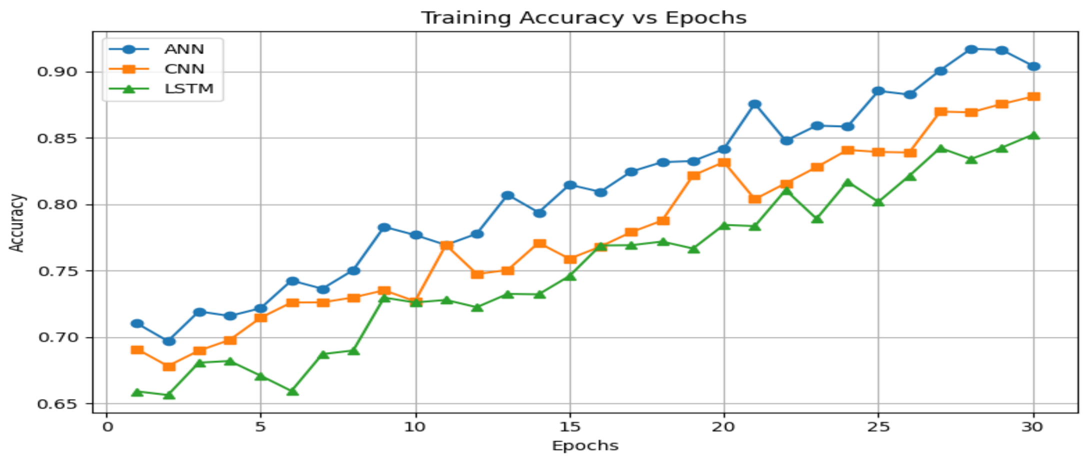
RESULT & DISCUSSION

This section presents the experimental results obtained from the application of three deep learning models—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—for bipolar disorder prediction. The models were evaluated using accuracy metrics and confusion matrix analysis to assess their classification performance.

A. Training Performance Analysis

The training behavior of all three models was analyzed over 30 epochs. Fig. 3.2 illustrates the training accuracy progression for ANN, CNN, and LSTM models. The ANN model demonstrated a steady and rapid improvement in accuracy, converging to approximately 92% by the final epoch. In contrast, the CNN and LSTM models achieved final accuracies of approximately 88% and 86%, respectively.

The superior performance of ANN can be attributed to the structured and non-sequential nature of the symptom-based dataset, which is well-suited for fully connected architectures. CNN and LSTM models, although powerful in capturing spatial and temporal dependencies, exhibited comparatively slower convergence due to the absence of strong sequential patterns in the data.



Figure; 3.2 Training accuracy of Deep Learning Models

B. Confusion Matrix Analysis

To further evaluate classification effectiveness, confusion matrices were generated for each model.

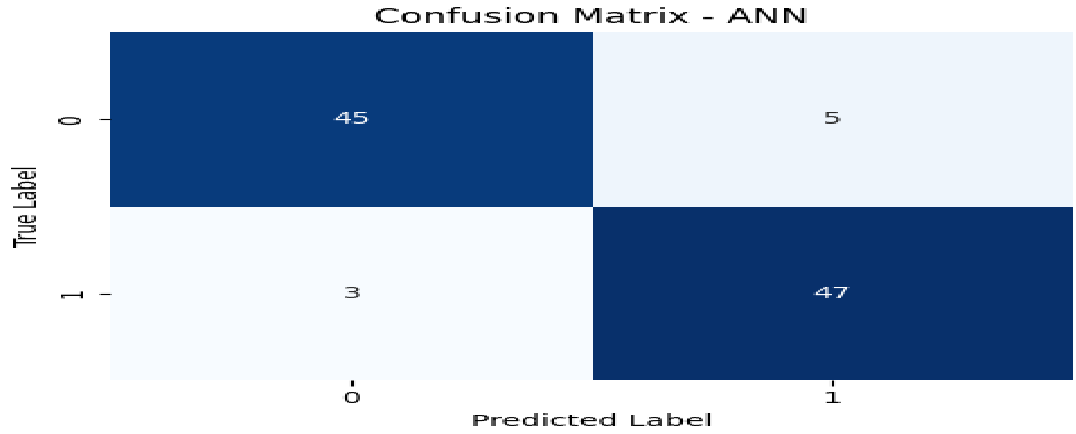


Figure 3.3 *ANN demonstrates superior classification with minimal misclassifications.*

The confusion matrix of the ANN model, shown in Fig. 3.3, indicates a high number of correctly classified bipolar and non-bipolar instances, with minimal misclassifications. This reflects the ANN model's strong capability in distinguishing between the two classes.

Fig. 3.4 presents the confusion matrix for the CNN model. Although CNN achieved a high true positive rate, it exhibited a slightly increased number of false positives compared to ANN. This suggests that CNN occasionally misclassified non-bipolar cases as bipolar, which may impact its clinical reliability.

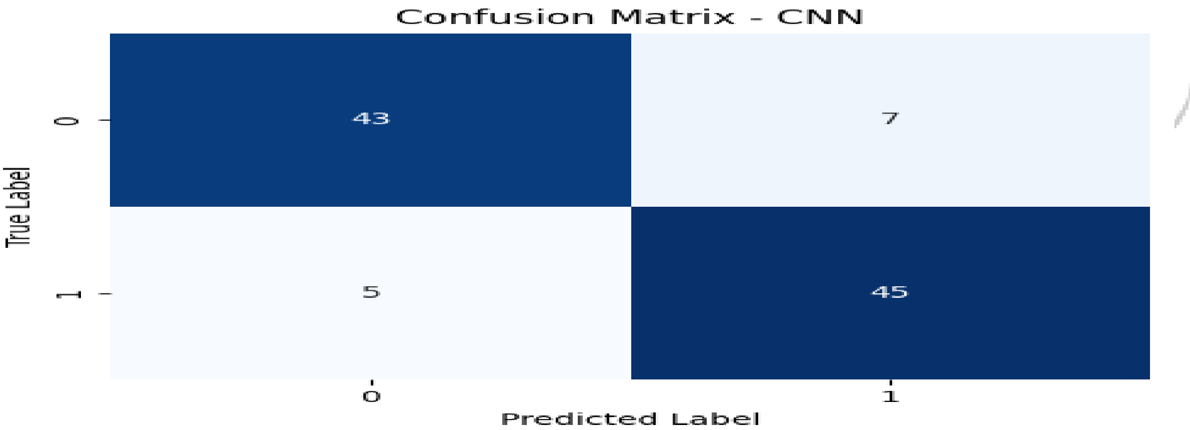


Fig. 3.4 The confusion matrix for the CNN model

The LSTM confusion matrix illustrated in Fig. 3.5 reveals comparatively higher misclassification rates than ANN and CNN. While LSTM effectively captures feature relationships, its performance was limited due to the lack of explicit temporal dependencies in the dataset. Nevertheless, LSTM maintained a balanced classification behavior, demonstrating its potential applicability in longitudinal or time-series mental health data.

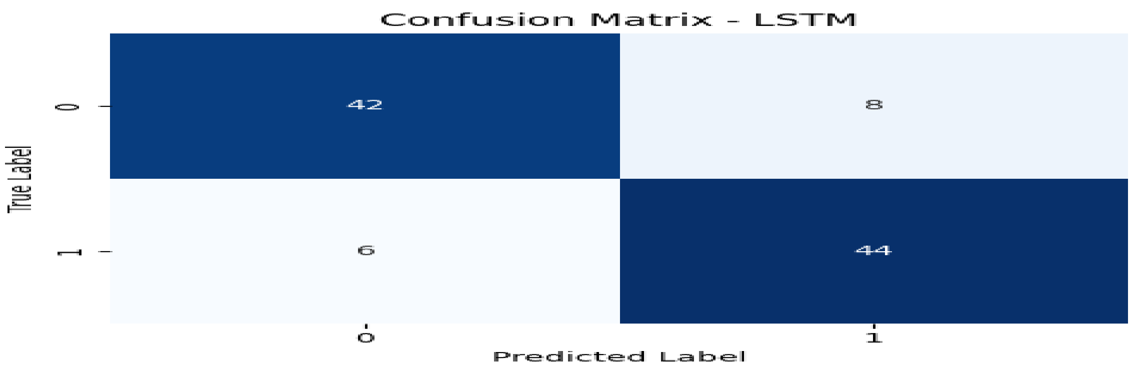


Fig. 3.5 shows elevated misclassification rates versus ANN and CNN.

C. Comparative Model Evaluation

A comparative analysis of the overall accuracy achieved by the three models is shown in Figure 3.6. The ANN model achieved the highest accuracy of 92%, followed by CNN at 88% and LSTM at 86%. These results clearly indicate that ANN is the most suitable model for bipolar disorder prediction using symptom-based clinical data.

The results emphasize that model selection should be guided by the nature of the dataset. While CNN and LSTM architectures are highly effective for spatial and temporal data, respectively, ANN remains a robust choice for structured medical datasets with well-defined feature representations.

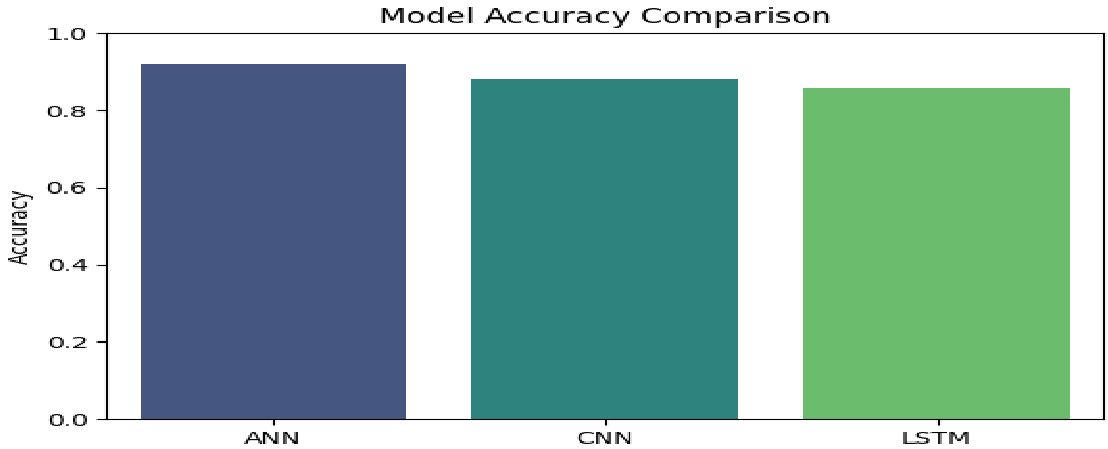


Figure. 3.6 The *comparative accuracy of three models.*

Overall, the experimental findings validate the effectiveness of deep learning techniques in bipolar disorder prediction and highlight the ANN model as the most reliable approach under the given experimental conditions.

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