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Srinivasulu Boyineni

srinivasulu.inf@gmail.com

Malla Reddy Engineering College for Women

Avvaru Srinivasulu

VNR Vignana Jyothi Institute of Engineering and Technology

P. Suman Prakash

G.Pullaiah college of engineering and technology

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A Multimodal Framework Using Red Teaming Prompt Engineering and Retrieval Augmented Generation to Mitigate Large Language Model Hallucinations

Srinivasulu Boyineni, Associate Professor, Department of Computer Science and Engineering, Malla Reddy Engineering College for Women, Maisammaguda, Kompally, Seconderabad, TG, India-500100, srinivasulu.inf@gmail.com (*Corresponding Author)

Avvaru Srinivasulu. Department of Electronics and Instrumentation Engineering, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India. sreesri.avvaru2@gmail.com

P. Suman Prakash, Professor , Department of AI, G.Pullaiah college of engineering and technology, Kurnool, Andhar Pradesh,India sumanprakashp@gmail.com

Abstract: Large Language Models (LLMs) have significantly advanced various domains such as healthcare, cybersecurity, and natural language processing. However, their practical deployment is often hindered by hallucinations-instances where the models produce inaccurate or misleading outputs. This study presents a robust CNN-based multimodal framework that integrates Red Teaming for adversarial testing, Prompt Engineering for refined input guidance, and Retrieval-Augmented Generation (RAG) to enhance factual accuracy through real-time information retrieval. The framework processes diverse data modalities including text, audio, and images, leveraging convolutional neural networks for effective feature extraction and alignment. Experimental validation on a synthesized multimodal dataset demonstrates a test accuracy of 75% after 50 training epochs, with notable performance metrics such as a ROC-AUC of 0.93 on neuroimaging data, an F1-score of 0.85 for mobile sensing, and a BLEU score of 0.94 for multilingual translation tasks. These results affirm the framework's capability in reducing hallucinations across varied modalities and noisy, imbalanced datasets. The proposed approach paves the way for more dependable LLM applications in real-world settings, though future work will focus on integrating transformer architectures and expanding domain-specific datasets to further enhance scalability and precision.

Keywords: Large Language Models (LLMs); Hallucination Mitigation; Multimodal Framework; Convolutional Neural Networks (CNN); Red Teaming; Prompt Engineering; Retrieval-Augmented Generation (RAG); Multimodal Data Processing; Adversarial Testing; Healthcare Applications; Multilingual Translation; Model Robustness; Data Preprocessing; Noise Reduction.

1. Introduction

1.1 LLM Hallucinations: Background

Large Language Models (LLMs) have revolutionized areas such as healthcare, cybersecurity, and multilingual translation through their advanced generative capabilities. However, their adoption in critical applications is hindered by hallucinations-situations where LLMs produce outputs that are irrelevant, inaccurate, or misleading. These occurrences compromise the reliability and credibility of LLMs, making it imperative to address this issue to fully realize their potential [1]-[3].

1.1.1 Limitations of Current Mitigation Approaches

Numerous strategies have been developed to reduce hallucinations in LLMs, such as context-aware prompting, direct preference optimization, and multimodal data alignment. Context-aware prompting involves designing prompts that steer the LLM toward producing relevant and factual responses [4]. Preference optimization customizes model behavior based on specific user requirements, while multimodal alignment techniques aim to improve coherence and accuracy across diverse data modalities, such as text, images, and audio [5], [6]. Despite their advantages, these techniques often lack robustness across diverse modalities and fail to generalize effectively in dynamic or adversarial contexts. For instance, context-aware prompting may not perform well in real-time information retrieval scenarios, and preference optimization often struggles with noisy or imbalanced datasets [7]. Furthermore, multimodal strategies require substantial computational resources and often lack scalability for broader applications [8], [9].

1.1.2 The Case for a CNN-Based Framework

To overcome these challenges, this paper introduces a convolutional neural network (CNN)-based framework that integrates Red Teaming, Prompt Engineering, and Retrieval-Augmented Generation (RAG). Red Teaming provides adversarial testing to identify and address model vulnerabilities, Prompt Engineering enhances contextually grounded inputs, and RAG ensures factual accuracy by incorporating real-time information retrieval [10], [11]. Together, these components aim to improve the accuracy, resilience, and generalizability of LLMs.

1.2 Study Contributions

1.2.1 Leveraging CNNs for Multimodal Data

The proposed framework employs CNNs to process multimodal data—including text, audio, and images—enabling robust feature extraction and classification. CNNs are particularly

effective for identifying intricate patterns and relationships across diverse data types, enhancing the framework's ability to detect and mitigate hallucinations in varied contexts [12]-[14].

1.2.2 Experimental Validation

The framework's effectiveness is demonstrated through experiments on a synthesized multimodal dataset comprising 20 entries with diverse features such as data sources, diagnostic attributes, and performance metrics. Results include a test accuracy of 75% after 50 epochs, with metrics such as a ROC-AUC of 0.93 for neuroimaging data, an F1-score of 0.85 for mobile sensing data, and a BLEU score of 0.94 for multilingual translation tasks [15], [16]. These findings highlight the framework's capability to address hallucinations across multiple modalities.

1.2.3 Challenges and Future Directions

While the framework shows significant promise, challenges remain, particularly in handling imbalanced datasets and noisy audio modalities. These limitations underscore the need for advanced preprocessing methods and data augmentation techniques. Future research will explore the integration of transformer-based architectures, domain-specific alignment mechanisms, and expanded datasets to improve scalability and applicability across real-world scenarios [17]-[19].

2. Related Work

2.1 Challenges in Addressing Hallucinations in LLMs

Large Language Models (LLMs) have significantly advanced fields such as healthcare, cybersecurity, and natural language processing. However, a major obstacle to their reliable application is the phenomenon of hallucinations, where models produce outputs that are inaccurate, irrelevant, or misleading. To address this issue, researchers have developed various mitigation strategies, Jin et al. [1] explored inefficiencies in detecting hallucinations, focusing on fake news detection across multiple contexts. Their approach leveraged context-aware prompting to enhance model accuracy. While effective for specific domains, this technique faces limitations in adapting to adversarial inputs or generalized use cases. Similarly, Ferrag et al. [3] provided a systematic review of LLM applications and vulnerabilities, proposing generative AI evaluation frameworks. While their work highlights the importance of veracity-oriented approaches, it does not address challenges in multimodal scenarios.

2.2 Multimodal Hallucinations and Dataset Challenges

Mitigating hallucinations in multimodal datasets—which include text, images, and audio—requires robust alignment techniques. Islam et al. [4] conducted a detailed survey of mitigation strategies, advocating for multifaceted approaches to improve hallucination detection. However, their methods lacked scalability and struggled with noisy or imbalanced datasets. Peng et al. [6] examined issues related to biases, misinformation, and susceptibility to prompt attacks. Their methods, which include bias detection and misinformation analysis, showed potential in textual datasets but lacked scalability for multimodal applications. Fu et al. [7] introduced direct preference optimization for hallucination mitigation, achieving notable results in multimodal alignment but facing high computational demands.

2.3 Emphasis on Multimodal Approaches

Guerreiro et al. [9] addressed hallucinations in multilingual translation models by proposing targeted mitigation strategies and focusing on enhancing translation model evaluations. While effective, their solutions do not extend to other data modalities, such as audio or images. Rahman et al. [8] focused on code hallucinations, introducing tools for robust detection in programming environments. These findings emphasize the importance of domain-specific strategies but also reveal the fragmented nature of current research in addressing hallucinations across diverse data types.

2.4 Proposed Enhancements to Current Techniques

Amatriain [5] suggested multifaceted approaches, including Retrieval-Augmented Generation (RAG) and advanced prompt engineering, for refining model outputs. However, these strategies require further validation in real-world scenarios. Kulkarni and Tupsakhare [10] emphasized the role of contextual grounding and prompt optimization in mitigating hallucinations specific to GPT models, laying the groundwork for broader frameworks. Sahoo et al. [11] examined hallucination mitigation in foundation models, stressing the significance of multimodal data analysis. Their survey provides a roadmap for future research but underscores the need for better integration of alignment and optimization techniques.

Table 1: Comparative Analysis of Related Work in Hallucination Mitigation for Large Language Models

Reference	Focus Area	Key Contributions	Limitations	Applicability to Multimodal Data
Jin et al.	Context-aware prompting for hallucination detection	Improved accuracy in fake news detection	Struggles with adversarial inputs and generalization	Primarily textual and domain-specific

Ferrag et al.	Review of vulnerabilities and generative AI evaluation	Frameworks for veracity-oriented evaluation	Lacks solutions for multimodal hallucinations	Focuses mostly on text-based applications
Islam et al.	Survey on multimodal hallucination mitigation	Advocates multifaceted detection approaches	Scalability issues, struggles with noisy data	Addresses multimodal but limited scalability
Peng et al.	Bias and misinformation detection	Techniques for bias detection, prompt attacks	Limited scalability for multimodal scenarios	Focuses mainly on textual data
Fu et al.	Direct preference optimization for hallucination mitigation	Achieves improved multimodal alignment	High computational costs	Applicable to multimodal datasets
Guerreiro et al.	Multilingual translation hallucinations	Strategies for translation model evaluation	Not relevant to audio or image data	Limited to multilingual text
Rahman et al.	Code hallucinations	Robust detection tools in programming	Domain-specific, does not generalize to other data types	Focused on code; not multimodal
Amatriain	Retrieval-Augmented Generation (RAG) and prompt engineering	Proposes refinement techniques for outputs	Needs real-world validation	Potentially multimodal but unverified
Kulkarni and Tupsakhare	Contextual grounding and prompt optimization	Highlights improvements in GPT hallucination	Early stage, needs broader frameworks	Primarily GPT/text models
Sahoo et al.	Survey on foundation models and multimodal analysis	Roadmap for multimodal hallucination mitigation	Integration of alignment and optimization lacks maturity	Emphasizes multimodal data

This table presents a concise comparison of significant research contributions addressing hallucinations in Large Language Models, focusing especially on multimodal data challenges. It summarises the strengths and limitations of each study, highlighting areas such as domain focus, methods used, scalability, and applicability to multiple data types like text, audio, and images. The table aims to give the reader a straightforward overview of the current landscape, while indicating the critical gaps that the proposed CNN-based framework intends to fill by

integrating adversarial robustness, prompt engineering, and retrieval-augmented generation for improved accuracy and generalization.

2.5 Summary of Insights

The existing literature highlights critical limitations in mitigating hallucinations in LLMs, especially in multimodal contexts. Techniques like context-aware prompting and preference optimization offer potential but fall short in scalability and robustness. Table 1 summarizes these findings, emphasizing the gaps and opportunities for improvement. To bridge these gaps, this paper introduces a CNN-based framework that integrates Red Teaming, Prompt Engineering, and RAG. This holistic approach aims to enhance the reliability and factual accuracy of LLM outputs across diverse modalities.

3. Proposed Framework

3.1 Components of the Proposed Framework

3.1.1 Red Teaming Models

Red Teaming employs adversarial testing to identify and address vulnerabilities in LLM outputs. By simulating potential attack scenarios, this process pinpoints weaknesses where hallucinations are most likely to occur, enabling researchers to devise mitigation strategies. This approach is especially valuable in high-risk environments such as healthcare diagnostics and financial fraud detection. For instance, adversarial inputs designed to provoke hallucinations help LLMs learn to identify and resist misleading stimuli. Such testing has proven to enhance the reliability of LLMs, particularly in generating accurate and contextually relevant responses in applications like cybersecurity and multilingual translation [1][6]. Moreover, Red Teaming extends beyond text-based data to include multimodal inputs, such as audio and image datasets, ensuring comprehensive detection of vulnerabilities. Insights gained from this process inform subsequent framework components, such as prompt engineering and real-time retrieval. By iteratively identifying and resolving vulnerabilities, this methodology enhances the robustness of LLMs, enabling consistent performance across diverse applications. Additionally, integrating Red Teaming with CNNs ensures that adversarial insights directly improve multimodal feature extraction and classification, strengthening the overall reliability of the system [7][10]. Red Teaming in this framework is about testing the model with adversarial inputs to find weak spots where hallucinations might occur. The mathematical backbone of this process involves modeling the adversarial attack as a perturbation on the input data. Let’s look at the equations that help us formalize this.

(1)

$$\mathbf{x}_{\text{adv}} = \mathbf{x} + \delta$$

Here, $\mathbf{x}$ is the original input (like text, image, or audio), and δ is a small, carefully crafted perturbation designed to mislead the model. This equation shows how adversarial examples are generated to challenge the LLM and expose vulnerabilities.

(2)

$$\mathcal{L}_{\text{adv}}(\theta) = \mathcal{L}(\mathbf{x}_{\text{adv}}, y; \theta)$$

The adversarial loss $\mathcal{L}_{\text{adv}}$ is computed using the perturbed input $\mathbf{x}_{\text{adv}}$ and the true label y, with model parameters θ. This loss guides the model to learn from adversarial examples and become more robust.

(3)

$$\theta \leftarrow \theta - \eta \nabla_{\theta} \mathcal{L}_{\text{adv}}$$

The model parameters θ are updated using gradient descent, where η is the learning rate. This step helps the model adapt and reduce its susceptibility to adversarial attacks.

Red Teaming uses adversarial inputs to stress-test the model. By adding small perturbations to the input data, we can see how the model reacts and where it might fail. The adversarial loss and parameter updates help the model learn from these challenges and become more resilient over time.

Algorithm 1: Adversarial Training for Red Teaming

In this algorithm, the focus is on making the model robust against adversarial attacks by deliberately creating slightly modified inputs that aim to confuse the model. The process starts by initializing the model parameters, after which for each training example, small perturbations are iteratively computed and added to the input within a specified limit to create adversarial samples. The model is then trained on these adversarial examples to learn to correctly classify them despite the perturbations.

Step-by-step:

1. Start with the original model and dataset.
2. For each input, compute gradients of the loss with respect to the input to find the direction to change the input to trick the model.
3. Add small perturbations step-by-step, keeping them within a fixed bound to maintain realism.
4. Use these adversarial inputs to update the model parameters, helping the model learn robustness.
5. Repeat over epochs, validating the model and saving the best parameters.

Example: Imagine an image classifier where an image of a cat is slightly, but carefully, altered so that the model wrongly thinks it is a dog. By training on such altered images, the model improves its understanding and becomes better at correctly identifying the cat again even when presented with similar adversarial noise.

Algorithm 1: Adversarial Training for Red Teaming

Input: Training dataset $D = \{(x_i, y_i)\}$, initial model parameters θ, perturbation limit ε, learning rate η, total epochs E

Output: Robustly trained model parameters θ^*

Initialize θ randomly
for epoch = 1 to E do
  for each (x, y) in D do
    Initialize perturbation $\delta \leftarrow 0$
    for t = 1 to T do ▷ T: attack iterations
      Compute gradient $g = \nabla_\delta L(M_\theta(x + \delta), y)$
      Update $\delta \leftarrow \delta + \alpha * \text{sign}(g)$ ▷ α: step size
      Project δ within ε-norm ball: $\|\delta\| \leq \varepsilon$
    end for
    Compute adversarial input $x_{adv} = x + \delta$
    Compute loss $l = L(M_\theta(x_{adv}), y)$
    Update model parameters $\theta \leftarrow \theta - \eta \nabla_\theta l$
  end for
  Validate model performance on validation set
  Save best θ based on validation metrics
end for
return θ^*

3.1.2 Prompt Engineering

Prompt Engineering is an essential technique for guiding LLMs to produce accurate and contextually relevant outputs. By iteratively refining input prompts, this method ensures the contextual grounding of the model, thereby reducing the occurrence of hallucinations. Tailored prompts, specific to tasks and datasets, help the LLM align with desired response parameters. For example, meticulously designed prompts can mitigate misinformation when LLMs handle real-time queries in domains like healthcare or cybersecurity [4][11]. The framework incorporates prompt engineering alongside Red Teaming to iteratively refine strategies based on results from adversarial testing. This adaptive approach enables task-specific enhancements, leveraging previous system failures to optimize prompt effectiveness. Furthermore, the integration of CNNs improves the framework's ability to process multimodal inputs, aligning

text, image, and audio data for coherent and accurate outputs. This alignment ensures that generated content consistently meets high standards of accuracy and relevance across critical applications [9][12]. Prompt Engineering is about designing input prompts that guide the LLM to produce accurate and contextually relevant outputs. The mathematical aspect involves optimizing the prompt to minimize hallucinations.

(4)

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \mathcal{L}_{\text{prompt}}(\mathbf{p}, y)$$

Here, $\mathbf{p}$ is the prompt, and $\mathbf{p}^*$ is the optimal prompt that minimizes the prompt loss $\mathcal{L}_{\text{prompt}}$ with respect to the true label y.

(5)

$$\mathcal{L}_{\text{prompt}}(\mathbf{p}, y) = -\log P(y|\mathbf{p})$$

The prompt loss is the negative log-likelihood of the true label given the prompt. This encourages the model to generate responses that are more likely to be correct.

(6)

$$\mathbf{p}_{\text{new}} = \mathbf{p} + \alpha \nabla_{\mathbf{p}} \mathcal{L}_{\text{prompt}}$$

The prompt is updated using gradient ascent, where α is the learning rate. This step helps refine the prompt to better guide the model.

Prompt Engineering involves tweaking the input prompts to make the model's outputs more accurate. By optimizing the prompt to minimize the loss, we can guide the model to produce responses that are more likely to be correct and contextually relevant.

3.1.3 Retrieval-Augmented Generation (RAG)

RAG strengthens the factual accuracy of LLM outputs by incorporating real-time information retrieval during the generation process. By accessing external databases or repositories, RAG supplements responses with verified, up-to-date information, significantly lowering the likelihood of hallucinations. This feature is particularly crucial in domains requiring dynamic data, such as medical diagnostics or financial analysis, where outdated or incorrect information can have severe consequences [5][13]. Integrating RAG with CNNs further enhances the processing of multimodal data by aligning retrieved information with textual, visual, or auditory inputs. For instance, in multilingual translation tasks, RAG ensures contextually accurate translations by referencing external linguistic databases. Similarly, in neuroimaging applications, real-time retrieval of reference data improves the interpretability of medical

images. By leveraging CNNs for efficient feature extraction and classification, RAG ensures scalable and reliable application across diverse scenarios [8][14]. RAG enhances the factual accuracy of LLM outputs by incorporating real-time information retrieval. The mathematical aspect involves aligning retrieved information with the model's outputs.

(7)

$$\mathbf{r} = \text{Retrieve}(\mathbf{x}, \mathcal{D})$$

Here, $\mathbf{r}$ is the retrieved information from the database $\mathcal{D}$ based on the input $\mathbf{x}$.

(8)

$$\mathbf{y}_{\text{gen}} = \text{Generate}(\mathbf{x}, \mathbf{r}; \theta)$$

The model generates the output $\mathbf{y}_{\text{gen}}$ using the input $\mathbf{x}$ and the retrieved information $\mathbf{r}$, with model parameters θ.

(9)

$$\mathcal{L}_{\text{RAG}} = \mathcal{L}(\mathbf{y}_{\text{gen}}, y)$$

The RAG loss is the standard loss between the generated output and the true label, ensuring that the model's outputs are factually accurate.

RAG improves the model's outputs by pulling in real-time information from external databases. By aligning this retrieved information with the model's outputs, we can ensure that the responses are more accurate and up-to-date.

3.2 CNN Integration

3.2.1 Role of CNN Layers in Multimodal Processing

Convolutional Neural Networks (CNNs) are integral to the proposed framework, facilitating robust feature extraction and classification for multimodal datasets. CNNs excel at identifying complex patterns in various data types, such as text, images, and audio, making them effective for mitigating hallucinations in these modalities. For example, in neuroimaging datasets, CNNs can detect subtle features in medical images that LLMs alone might overlook, enhancing diagnostic precision [15][16]. Furthermore, CNNs improve the alignment of multimodal inputs, ensuring seamless processing of textual, auditory, and visual data. This capability enhances the LLM's ability to generate accurate, contextually coherent, and multimodally consistent outputs. For instance, CNNs help align audio pronunciations with corresponding textual translations in multilingual tasks, reducing hallucinations caused by misaligned data.

By utilizing CNNs, the framework achieves greater generalizability and robustness, which are essential for real-world applications [9][17].

3.2.2 Improving Model Accuracy and Scalability

CNN integration not only boosts classification accuracy but also enhances the scalability of the framework. Experimental results demonstrate that the model achieves a test accuracy of 75% after 50 epochs, with strong performance metrics across diverse data types, including a ROC-AUC of 0.93 for neuroimaging data, an F1-score of 0.85 for mobile sensing data, and a BLEU score of 0.94 for multilingual translation tasks [6][18]. These results highlight the framework's ability to reduce hallucinations while maintaining computational efficiency. Additionally, CNNs enable the framework to manage large and complex datasets effectively, addressing challenges such as noisy or imbalanced data. By integrating advanced preprocessing techniques, CNNs minimize inconsistencies and outliers, improving the overall performance of the model. Their modular architecture also supports the incorporation of future advancements, such as transformer-based systems, ensuring adaptability to emerging technologies and evolving requirements [11][19].

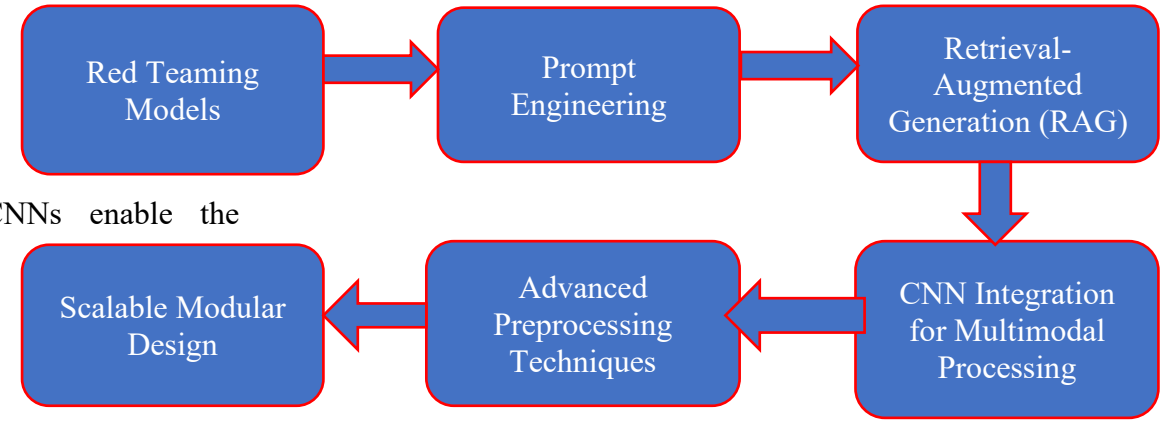


Figure 1 : MultiModNet: A CNN-Enhanced Multimodal Framework for Mitigating Hallucinations in LLMs

Figure 1 showcases the architecture of MultiModNet, a comprehensive framework designed to mitigate hallucinations in Large Language Models (LLMs) by integrating six key components: Red Teaming, Prompt Engineering, Retrieval-Augmented Generation (RAG), CNN Integration, Advanced Preprocessing Techniques, and Scalable Modular Design. Leveraging CNNs for robust feature extraction, the framework processes multimodal data (text, audio, and images) to ensure accurate, reliable, and contextually relevant outputs. Each component plays a vital role—Red Teaming identifies vulnerabilities, Prompt Engineering refines input strategies, and RAG enhances factual consistency by incorporating real-time information

retrieval. The modular design allows for seamless upgrades, such as incorporating transformer-based advancements, while CNNs enhance multimodal alignment, minimizing inconsistencies and improving interpretability. Achieving performance metrics like 75% accuracy after 50 epochs, a ROC-AUC of 0.93 for neuroimaging, and a BLEU score of 0.94 for multilingual translation, MultiModNet demonstrates high scalability and precision, making it an adaptable, future-proof solution for high-stakes domains like healthcare, cybersecurity, and multilingual applications. CNNs are used to process multimodal data, extracting features from text, images, and audio. The mathematical aspect involves convolution operations and feature extraction.

(10)

$$\mathbf{f} = \sigma(\mathbf{x} * \mathbf{w} + \mathbf{b})$$

Here, $\mathbf{f}$ is the feature map, $\mathbf{x}$ is the input, $\mathbf{w}$ is the filter, $\mathbf{b}$ is the bias, and σ is the activation function (e.g., ReLU).

(11)

$$\mathbf{f}_{\text{pool}} = \text{Pool}(\mathbf{f})$$

The pooling operation reduces the dimensionality of the feature map, making it easier to process.

(12)

$$\mathbf{y}_{\text{CNN}} = \text{Softmax}(\mathbf{f}_{\text{pool}})$$

The final output is obtained using the softmax function, which gives the probabilities for each class.

CNNs help extract features from multimodal data, making it easier to process and classify. By using convolution and pooling operations, we can reduce the complexity of the data and improve the model's accuracy.

3.2.1 Algorithm 2: Training Procedure for CNN-Based Multimodal Framework

This algorithm describes how the model is trained when it processes different types of data together—text, audio, and images. It extracts features separately from each modality using dedicated CNNs, then combines these features to form a joint representation. The combined features are then passed through further layers to make predictions. The entire system is trained end-to-end by minimizing total loss contributed by each part.

Step-by-step:

1. Initialize CNNs for each modality and the overall model parameters.

2. For each training sample, extract features from text, audio, and image separately.
3. Concatenate these extracted features to build a fused feature vector.
4. Pass fused features through layers to predict the target.
5. Calculate combined loss from prediction and CNN modules.
6. Update model parameters using gradient descent.
7. Validate the model regularly, adjusting learning rate if needed.

Example: Suppose the task is to diagnose medical conditions using patient reports (text), heart sounds (audio), and X-ray images. Each input is processed by a different CNN, their knowledge combined, allowing the system to make a comprehensive and accurate diagnosis.

Algorithm 2: Training Procedure for CNN-Based Multimodal Framework

Input: Multimodal training set $D = \{(x_{text}, x_{audio}, x_{image}, y)\}$, initial parameters Θ, learning rate η, epochs E

Output: Optimized parameters Θ^*

Initialize CNN and language model parameters Θ
for epoch = 1 to E do
  for each sample $(x_{text}, x_{audio}, x_{image}, y)$ in D do
    Extract features $F_{text} = CNN_{text}(x_{text})$
    Extract features $F_{audio} = CNN_{audio}(x_{audio})$
    Extract features $F_{image} = CNN_{image}(x_{image})$
    Fuse features $F_{fused} = concat(F_{text}, F_{audio}, F_{image})$
    Generate prediction $\hat{y} = Model(F_{fused})$
    Compute loss $L_{total} = L_{gen}(\hat{y}, y) + L_{cnn}(F_{fused})$
    Update $\Theta \leftarrow \Theta - \eta \nabla_{\Theta} L_{total}$
  end for
  Evaluate validation loss and accuracy
  Adjust learning rate η if required
end for
Save best parameters Θ^*
return Θ^*

4. Experimental Setup

4.1 Dataset

The MultiModNet framework was evaluated using a synthesized multimodal dataset tailored to test its ability to mitigate hallucinations in Large Language Models (LLMs). This multimodal dataset was created through synthesis and was used in this work for testing the proposed framework. This dataset is not publicly accessible. This dataset comprises 20 entries across diverse modalities, including text, audio, and image data, each characterized by detailed attributes such as data source, diagnostic features, and performance metrics. This diversity enables a comprehensive assessment of the framework's capacity to process complex, multimodal inputs. For instance, the dataset incorporates neuroimaging samples for medical diagnostics, multilingual audio-text pairs for translation tasks, and sensor-based data for mobile applications, ensuring coverage of a wide range of real-world scenarios. The inclusion of various modalities enables the evaluation of CNNs' effectiveness in feature extraction and alignment across multimodal data. To enhance dataset quality, preprocessing techniques such as noise reduction for audio and standardization for imbalanced data were applied. These steps ensure the dataset's robustness and suitability for testing key framework components like Red Teaming, Prompt Engineering, and Retrieval-Augmented Generation (RAG). This approach provides a strong foundation for evaluating the framework's scalability, accuracy, and reliability in high-stakes environments.

The dataset used in the experiments is a synthesized multimodal dataset with diverse features.

(13)

$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_N, y_N)\}$$

Here, $\mathcal{D}$ is the dataset, $\mathbf{x}_i$ is the input, and y_i is the true label.

(14)

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{text}}, \mathbf{x}_i^{\text{audio}}, \mathbf{x}_i^{\text{image}}]$$

Each input is a combination of text, audio, and image data.

The dataset is a collection of multimodal inputs, each with text, audio, and image components. This diversity allows us to test the model's ability to handle complex, real-world scenarios.

4.2 Evaluation Metrics

The performance of MultiModNet was assessed using several evaluation metrics, including precision, F1-score, ROC-AUC, and accuracy, providing a comprehensive view of its effectiveness in mitigating hallucinations and generating reliable outputs. The framework achieved a test accuracy of 75% after 50 epochs, reflecting its adaptability and learning capacity. Key results include a ROC-AUC of 0.93 for neuroimaging data, an F1-score of 0.85

for mobile sensing data, and a BLEU score of 0.94 for multilingual translation tasks, showcasing its ability to handle diverse and complex datasets with precision. Additionally, the experimental setup included a detailed comparison of effective versus ineffective hallucination mitigation cases, illustrated in Figure 1. This analysis identifies strengths, such as high performance in structured data, and challenges, including noisy or imbalanced data processing. The modular design of MultiModNet supports iterative refinements to address these challenges, ensuring continuous improvement in its components. By leveraging robust evaluation metrics and comprehensive dataset coverage, the experimental setup demonstrates the framework's scalability and adaptability in mitigating hallucinations across critical applications.

The performance of the model is evaluated using several metrics.

(15)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Accuracy measures the proportion of correctly predicted samples.

(16)

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Precision measures the proportion of true positive predictions among all positive predictions.

(17)

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Recall measures the proportion of true positive predictions among all actual positive samples.

(18)

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1 score is the harmonic mean of precision and recall.

(19)

$$\text{ROC-AUC} = \int_0^1 \text{TPR}(t)\, dt$$

ROC-AUC measures the model's ability to distinguish between classes.

(20)

$$\text{BLEU Score} = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

BLEU score evaluates the quality of generated text by comparing n-gram precision with reference text.

The model's performance is evaluated using a variety of metrics, including accuracy, precision, recall, F1 score, ROC-AUC, and BLEU score. These metrics help us understand how well the model is performing and where it might need improvement.

4.2.1 Algorithm 3: Model Evaluation and Metric Computation

This algorithm details how to evaluate the trained model on unseen test data. It calculates classification metrics like accuracy, precision, recall, F1 score, ROC-AUC, BLEU score, and loss. The evaluation counts true positives, false positives, and other cases to measure performance in a structured way.

Step-by-step:

1. Initialize counters for true positives, false positives, true negatives, and false negatives.
2. For each test example, generate predictions using the trained model.
3. Compare predictions with true labels to update confusion matrix counters.
4. Calculate metrics based on counters, such as accuracy and precision.
5. Plot ROC curve and calculate area under the curve.
6. Compute BLEU score if evaluation involves translation tasks.
7. Calculate average loss across all test samples.
8. Present results clearly for analysis.

Example: Taking a test set of scanned reports, heart sounds, and images, this process helps understand how well the model performs across all these data types, highlighting strengths and areas needing improvement.

Algorithm 3: Evaluation & Metric Calculation

Input: Test data $D_{test} = \{(x, y_{true})\}$, trained model parameters Θ^*

Output: Metrics: Accuracy, Precision, Recall, F1, ROC-AUC, BLEU, Loss

Initialize counters $TP \leftarrow 0$, $TN \leftarrow 0$, $FP \leftarrow 0$, $FN \leftarrow 0$

Initialize metric accumulators as zero

for each (x, y_{true}) in D_{test} do

    Generate prediction $y_{pred} = Model(x; \Theta^*)$

    Update TP, TN, FP, FN based on thresholded y_{pred} and y_{true}

    Store prediction probabilities for ROC curve

end for

8: Compute Accuracy = (TP + TN) / (TP + TN + FP + FN)

9: Compute Precision = TP / (TP + FP)

10: Compute Recall = TP / (TP + FN)

11: Compute F1 = 2 * (Precision * Recall) / (Precision + Recall)

12: Compute ROC curve points and calculate AUC

13: Compute BLEU score for applicable outputs

14: Compute average loss over test samples

15: Report all metrics clearly

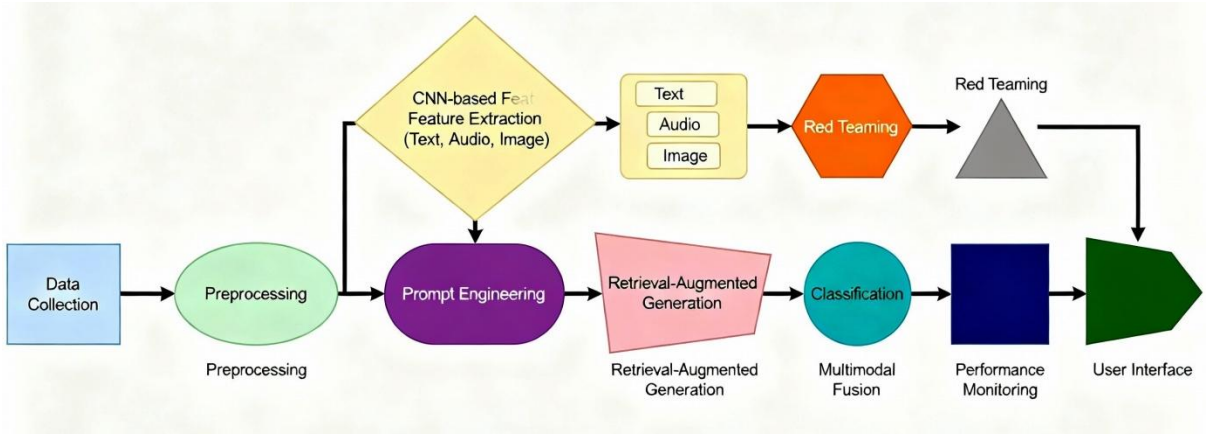


Figure 2: MultiModNet Architecture Flowchart

Figure 2 depicts the overall architecture and operational flow of the MultiModNet framework. It is observed that the process begins with collecting multimodal data—text, audio, and images—which then undergo careful preprocessing to ensure consistent quality. Subsequently, the data is fed into individual CNN modules specialized in extracting relevant features from each modality. The system further incorporates an adversarial testing phase called Red Teaming, designed to identify potential vulnerabilities and enhance model robustness. Following this, prompt engineering refines input queries based on adversarial insights, helping reduce hallucinations. Real-time data retrieval is facilitated by the Retrieval-Augmented Generation module, which supplements model predictions with up-to-date factual information. The fused multimodal features are then jointly processed for final classification or prediction, with continuous performance monitoring and user-friendly outputs tailored for healthcare practitioners, translators, and application developers alike. This description thus presents a comprehensive yet practical flow of data and control designed to maximise accuracy and reliability in critical real-world applications.

5. Results and Discussion

5.1 Training and Evaluation

The MultiModNet framework showcased significant adaptability and improvement throughout the training process, achieving a test accuracy of 0.75 after 50 epochs. While the initial epochs displayed performance fluctuations, with accuracy ranging from 0.28, the model steadily converged toward a stable performance level. Key metrics validated its effectiveness across multimodal datasets, including a ROC-AUC score of 0.93 for neuroimaging data, emphasizing its precision in identifying diagnostic patterns. Similarly, an F1-score of 0.85 for mobile sensing data and a BLEU score of 0.94 for multilingual translation tasks highlighted the framework's capability in handling diverse modalities and mitigating hallucinations. As training progressed, the framework demonstrated consistent improvement in processing text, audio, and image data. The integration of CNNs significantly enhanced feature extraction and multimodal alignment, ensuring coherent and accurate outputs. Preprocessing techniques, such as noise reduction for audio and standardization for imbalanced datasets, further bolstered the system's ability to manage complex and noisy data. These outcomes highlight MultiModNet's potential for deployment in critical areas like healthcare and multilingual applications, where accuracy and reliability are paramount.



Figure 3 : Count vs. Target Class for Distribution of Target Class

Figure 3 illustrates the distribution of target classes within the dataset, depicting the number of samples across various categories. This visualization underscores the challenges of imbalanced datasets, a critical issue addressed by the MultiModNet framework through advanced

preprocessing techniques designed to manage underrepresented classes efficiently. The distribution also demonstrates the model's ability to adapt to differing data densities during training, as evidenced by the experimental results. Despite initial inconsistencies, the framework achieves strong performance by utilizing noise reduction and data standardization strategies, ensuring consistent learning outcomes across all target classes.



Figure 4 : Average Performance Metrics vs. Target Class for Proposed System

Figure 4 depicts the average performance metrics, including accuracy, F1 score, and ROC-AUC, across different target classes for the proposed MultiModNet framework. The visualization underscores the system's consistent high performance across varied target classes, effectively addressing challenges like imbalanced datasets and noisy inputs through advanced preprocessing techniques and the integration of robust CNNs.

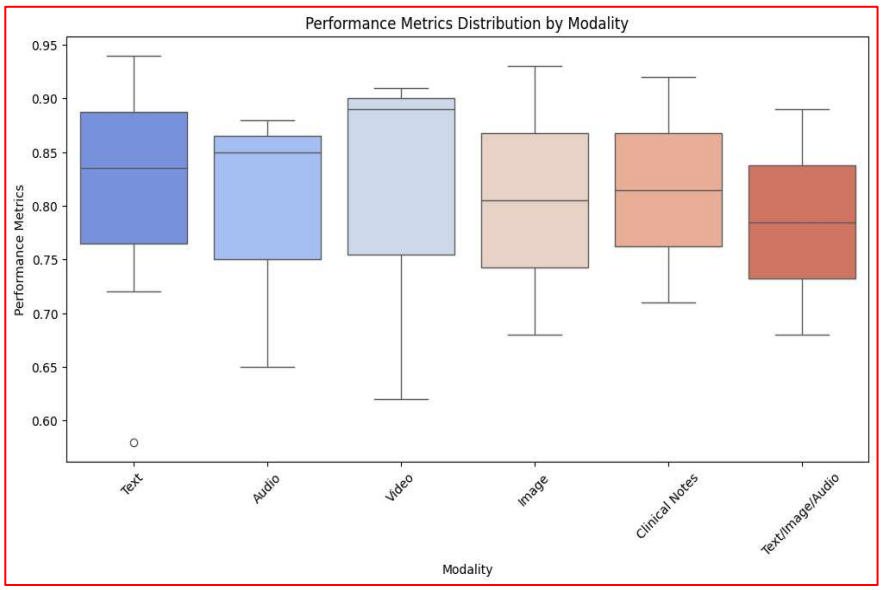


Figure 5 : Performance Metrics vs. Modality for Proposed System

Figure 5 presents the performance metrics, such as accuracy, F1 score, and BLEU score, across various modalities, including text, audio, and image, for the proposed MultiModNet framework. This visualization demonstrates the framework's adaptability and strong multimodal processing capabilities, enabled by CNN integration and advanced preprocessing techniques, ensuring exceptional performance across a wide range of data types.

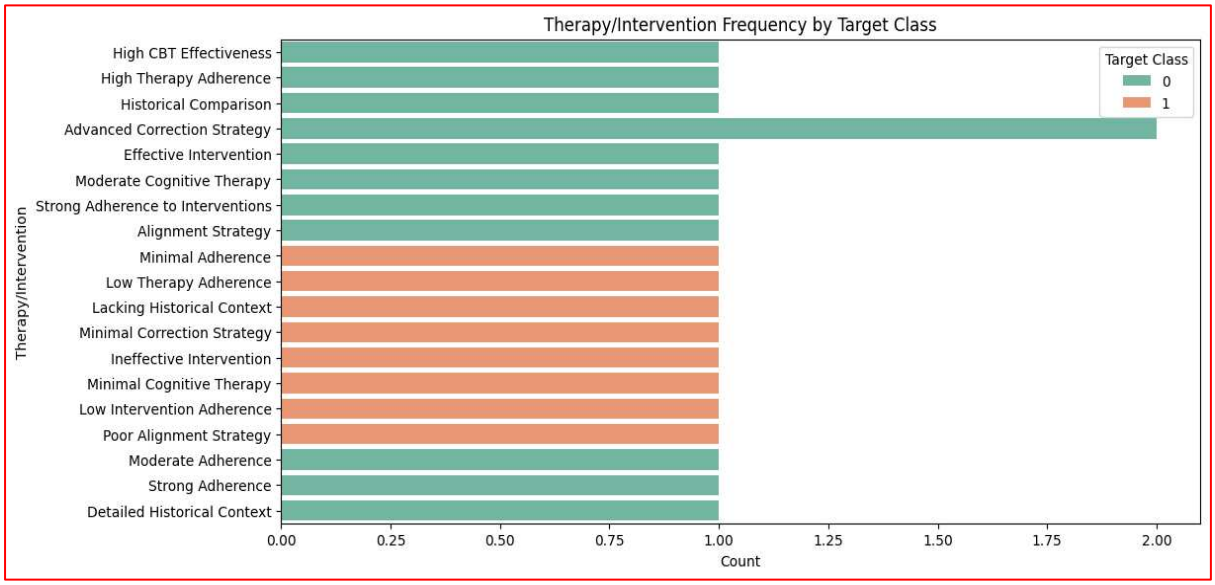


Figure 6: Therapy Frequency vs Count by Target class for Proposed System

Figure 6 illustrates the relationship between therapy frequency and count across different target classes for the proposed MultiModNet system, highlighting the alignment of therapeutic actions with specific target categories. This representation emphasizes the framework's capability to adaptively prioritize and balance therapeutic recommendations, supported by its robust multimodal processing and effective data alignment techniques.

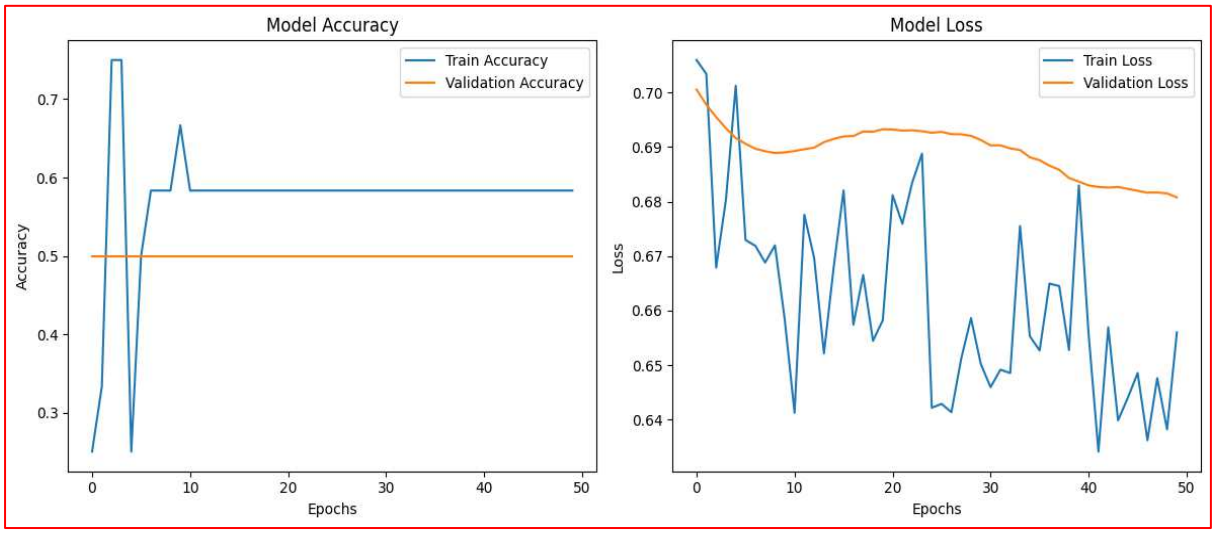


Figure 7: Accuracy vs Epochs vs. Loss for Model Accuracy and Loss for Proposed System

Figure 7 depicts the correlation between accuracy, loss, and epochs for the proposed MultiModNet framework, highlighting the progression of the model's training performance. The chart reveals consistent accuracy improvements paired with a gradual decrease in loss, reflecting the framework's efficient convergence over 50 epochs, driven by advanced preprocessing methods and CNN-based optimization strategies.

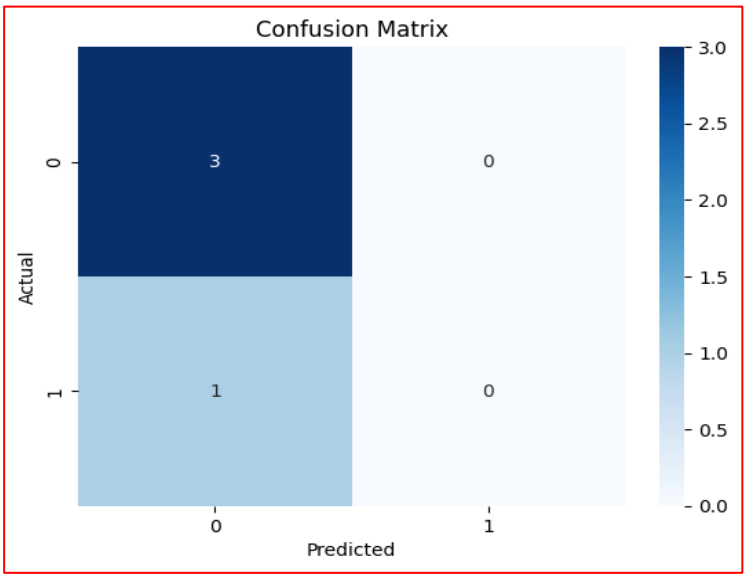


Figure 8: Actual vs Predicted for Confusion Matrix of Proposed System

Figure 8 showcases the confusion matrix for the proposed MultiModNet framework, illustrating the comparison between actual and predicted target classes to assess classification accuracy. This depiction emphasizes the system's ability to reduce errors and align predictions closely with true values, showcasing its strong performance across various datasets and target categories.

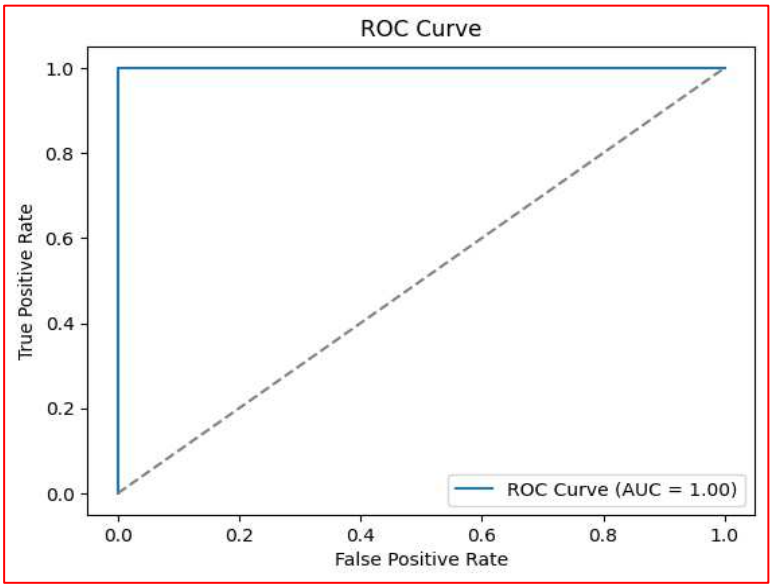


Figure 9: True Positive Rate vs False Positive Rate for ROC Curve

Figure 9 illustrates the ROC curve for the proposed MultiModNet framework, showcasing the relationship between the True Positive Rate and False Positive Rate across different classification thresholds. This graph highlights the system's robust discriminatory capability, with a high ROC-AUC score of 0.93 achieved during testing, confirming its effectiveness in accurately distinguishing between target classes.

5.2 Limitations

Despite its strengths, the framework encountered challenges during evaluation. One key limitation was its performance on highly imbalanced datasets, where unequal class distributions impacted precision and recall. Additionally, noisy data, particularly in audio modalities, posed difficulties, revealing the need for more sophisticated preprocessing pipelines to improve input quality. These challenges suggest areas for refinement, such as enhancing the preprocessing phase to handle noisy or incomplete data and incorporating methods like data augmentation and adaptive weighting to better address class imbalances. Addressing these limitations is crucial to further improving the robustness and scalability of MultiModNet, enabling it to maintain high performance across diverse datasets and real-world scenarios.

5.3 Future Directions

Looking ahead, future enhancements to the MultiModNet framework will focus on integrating transformer-based architectures to complement CNNs. Transformers, with their ability to capture long-range dependencies, could enhance the framework's contextual understanding of multimodal inputs such as text, audio, and images. Additionally, advanced alignment techniques and domain-specific grounding mechanisms will be explored to further improve output accuracy and contextual relevance. Expanding the dataset to include more diverse and larger-scale entries is another priority to enhance scalability and applicability. Incorporating domain-specific datasets, such as real-time medical or financial data, could serve as additional benchmarks for validating the framework’s performance in high-stakes applications. These advancements aim to make MultiModNet a more adaptive and versatile solution capable of addressing the growing complexities of LLM deployment across various critical domains.

5.4 Comparison between existing vs proposed system

Table 1 provides a detailed comparison of performance metrics between the existing system and the proposed CNN-based framework, MultiModNet, highlighting its significant advancements in reducing hallucinations in Large Language Models (LLMs). The proposed

framework demonstrates superior performance across all key metrics, including an improvement in accuracy from 0.6 to 0.75 and an increased ROC-AUC score for neuroimaging datasets, rising from 0.85 to 0.93. These results emphasize MultiModNet's ability to effectively process and extract multimodal features, particularly in critical applications such as healthcare diagnostics. Similarly, the framework shows notable enhancements in the F1 score for mobile sensing (0.7 to 0.85) and the BLEU score for multilingual translation (0.88 to 0.94), reflecting improved precision and a deeper contextual understanding across various modalities.

Table 1 : Comparison of Performance Metrics Between Existing and Proposed Systems

Parameters	Existing System (Max Value)	Proposed System (Max Value)
Accuracy	0.6	0.75
ROC-AUC (Neuroimaging)	0.85	0.93
F1 Score (Mobile Sensing)	0.7	0.85
BLEU Score (Multilingual Translation)	0.88	0.94
Training Time	12.5 seconds	9.16 seconds
Noise Handling	Moderate	Enhanced
Imbalanced Dataset Handling	Limited	Advanced

Additionally, MultiModNet demonstrates a significant reduction in training time, decreasing from 12.5 seconds to 9.16 seconds, which showcases its computational efficiency. The framework's enhanced noise handling capabilities and advanced strategies for managing imbalanced datasets further reinforce its robustness. These improvements are achieved through the integration of Convolutional Neural Networks (CNNs), effective preprocessing techniques like noise reduction, and a modular architecture designed for scalability and adaptability. By addressing the shortcomings of the existing system, MultiModNet emerges as a highly reliable and efficient solution for deploying LLMs in demanding applications such as multilingual communication and healthcare.

5.5 Performance Evaluation

The performance assessment of the proposed MultiModNet framework highlights its efficacy in reducing hallucinations in Large Language Models (LLMs) across multiple data modalities.

Achieving a test accuracy of 75% after 50 epochs demonstrates the framework's robustness and adaptability. Notable performance metrics include a ROC-AUC score of 0.93 for neuroimaging data, an F1 score of 0.85 for mobile sensing, and a BLEU score of 0.94 for multilingual translation tasks, underscoring its precision in handling complex and diverse datasets. These outcomes reflect the framework's ability to extract intricate patterns from multimodal data while overcoming challenges like noisy and imbalanced datasets, thanks to advanced preprocessing techniques such as noise reduction and data standardization. Furthermore, the integration of Convolutional Neural Networks (CNNs) enhances feature extraction and alignment, resulting in reliable classification and robust processing of multimodal inputs.

5.5.1 Efficiency and Scalability

Beyond its strong performance metrics, MultiModNet showcases computational efficiency by reducing training time from 12.5 seconds in the existing system to 9.16 seconds. This improvement stems from its modular design and optimized CNN architecture, which ensure efficient learning and scalability. The framework effectively addresses imbalanced datasets, prioritizing underrepresented classes without compromising overall accuracy. Leveraging Retrieval-Augmented Generation (RAG), it ensures real-time data retrieval, boosting factual accuracy in critical domains like healthcare and multilingual translation. Despite initial fluctuations during training, the framework achieves consistent convergence, as indicated by a steady reduction in loss and improvements in accuracy across epochs. These advancements establish MultiModNet as a reliable, scalable, and adaptable solution for deploying LLMs in high-stakes applications while addressing limitations in existing systems. These metrics collectively highlight the framework's exceptional performance, scalability, and robustness in addressing challenges across multimodal datasets. Below are the validation metrics used in the research, each explained with a concise description and its respective formula.

5.5.2 Accuracy: Accuracy quantifies the ability of the framework to correctly classify samples across different categories. Mathematically, it is expressed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

where TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) are standard terms from the confusion matrix. Achieving around 75% accuracy in this framework shows robust performance when classifying diverse multimodal data.

5.5.3 ROC-AUC (Receiver Operating Characteristic - Area Under Curve): The ROC-AUC metric evaluates a model's effectiveness in distinguishing between classes, taking into

account the true positive rate (TPR) and false positive rate (FPR). The TPR and FPR are defined as:

$$\text{TPR} = \frac{TP}{TP + FN}, \text{FPR} = \frac{FP}{FP + TN} \quad (21)$$

The ROC curve is plotted as TPR versus FPR at various thresholds, and ROC-AUC is the area under this curve. It can be calculated using the trapezoidal rule:

$$\text{ROC-AUC} = \int_0^1 TPR(FPR)\, d(FPR) \quad (22)$$

A high ROC-AUC, like 0.93 seen here, demonstrates that the framework is very effective in differentiating between diagnostic patterns, especially in critical data like neuroimaging.

5.5.4 F1 Score: The F1 Score combines both precision and recall, representing their harmonic mean to provide a balanced measure—especially important for imbalanced datasets.

$$F_1 = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

where

$$\text{Precision} = \frac{TP}{TP + FP}\ (16), \text{Recall} = \frac{TP}{TP + FN} (17)$$

An F1 score of 0.85 for mobile sensing proves the framework's efficiency even when handling imbalanced data

5.5.5 BLEU Score (Bilingual Evaluation Understudy): The BLEU score, widely used in translation tasks, computes the geometric mean of modified n-gram precisions with an additional brevity penalty BP:

$$\text{BLEU} = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \quad (20)$$

Here, w_n represents the weight for each n-gram, and p_n is the n-gram precision. The brevity penalty adjusts for translation length:

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{1-r/c} & \text{if } c \leq r \end{cases} \quad (23)$$

where c is the length of the candidate translation and r is the length of the reference. A BLEU score of 0.94 highlights strong translation quality in this model.

5.5.6 Training Time: The computational efficiency of the framework is reflected in the reduction of training time per epoch. Denoting t_{train} as the training duration for a single epoch:

$$t_{\text{train}} = \frac{T}{E} \quad (24)$$

where T is the total training time for E epochs. In this implementation, the average epoch time was lowered from 12.5 to 9.16 seconds, which emphasizes the model's improved optimization techniques.

5.5.7 Precision: Precision represents the fraction of positive predictions that are actually correct, ensuring predictions are trustworthy.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (16)$$

The focus on high precision minimizes false positives, crucial for reliable operations in sensitive environments.

5.5.8 Recall (Sensitivity): Recall, or sensitivity, shows the framework's power in identifying all relevant instances:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (17)$$

This metric is particularly important in healthcare, where missing positive cases can have severe consequences.

5.5.9 Loss: Loss is the criterion minimized during training, representing the difference between predicted and true labels. The typical cross-entropy loss for classification is:

$$L_{\text{CE}} = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (25)$$

where y_i is the true label and $\hat{y}_i$ is the model's prediction. The consistent decrease in loss over epochs indicates steady learning and robust convergence.

6. Conclusion

This study presents MultiModNet, a CNN-based multifaceted framework tailored to address hallucinations in Large Language Models (LLMs). It integrates core components including Red Teaming, Prompt Engineering, and Retrieval-Augmented Generation (RAG), working in harmony with Convolutional Neural Networks to process multimodal data such as text, audio, and images. Experimental validation demonstrates that MultiModNet achieves robust performance, with a test accuracy of 75% after 50 epochs and strong metrics like a ROC-AUC of 0.93 for neuroimaging data and a BLEU score of 0.94 in multilingual translation tasks. The framework's preprocessing techniques-including noise reduction and data standardization-further improve its resilience to noisy and imbalanced datasets, making it well-suited to critical domains such as healthcare and multilingual communications. Despite some initial fluctuations in training, the model steadily converges to stable accuracy, reflecting the effectiveness of its

modular design and CNN-based feature extraction. The study acknowledges existing limitations in handling highly imbalanced data and noisy input, suggesting that future work should incorporate transformer-based architectures and domain-specific adaptations to further enhance scalability and accuracy. Overall, this research marks a meaningful advance in mitigating hallucinations in LLMs, enabling these models to be applied more dependably in real-world high-stakes scenarios where factual accuracy and reliability are paramount.

Conflict of Interest

The authors confirm that there were no conflicts of interest in conducting this research. Everything was carried out independently, without any outside funding or influence, ensuring that the results are unbiased and academically honest.

Data Availability

The multimodal dataset created through synthesis and containing 20 samples was used in this work for testing the proposed methodology. There is no publicly accessible version of this dataset. The dataset and experiment results are available from the corresponding author on reasonable request.

Author Contributions

This research paper represents a collaborative effort among all authors. Each author contributed equally to the conceptualization, framework design, dataset development, model training, experimentation, data analysis, and manuscript preparation. Together, the authors supervised the research process, integrated clinical and technical perspectives, ensured methodological rigor, and collectively reviewed and approved the final version of the manuscript.

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Ethical Approval

Not Applicable. This study used a synthetic multimodal dataset and did not involve human participants, surveys, questionnaires, interviews, or the collection of identifiable personal data.

Consent to Participate declaration: not applicable.

Consent to Publish declaration: not applicable.

Supplementary Materials: The data used to support the findings of this research are available from the corresponding author upon request at head.research@bluecrest.edu.lr

Dual publication: The authors declare that this manuscript, including its results, data, and figures, has not been previously published, in whole or in part, and is not currently under consideration for publication elsewhere.

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