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Adaptive Feature Fusion: Enhancing Generalization in Deep Learning Models

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Abstract

In recent years, deep learning models have demonstrated remarkable success in various domains, such as computer vision, natural language processing, and speech recognition. However, the generalization capabilities of these models can be negatively impacted by the limitations of their feature fusion techniques. This paper introduces an innovative approach, Adaptive Feature Fusion (AFF), to enhance the generalization of deep learning models by dynamically adapting the fusion process of feature representations.

The proposed AFF framework is designed to incorporate fusion layers into existing deep learning architectures, enabling seamless integration and improved performance. By leveraging a combination of data-driven and model-based fusion strategies, AFF is able to adaptively fuse features based on the underlying data characteristics and model requirements. This paper presents a detailed description of the AFF framework, including the design and implementation of fusion layers for various architectures.





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Extensive experiments are conducted on multiple benchmark datasets, with the results demonstrating the superiority of the AFF approach in comparison to traditional feature fusion techniques. The analysis showcases the effectiveness of AFF in enhancing generalization capabilities, leading to improved performance across different tasks and applications.

Finally, the paper discusses various real-world use cases where AFF can be employed, providing insights into its practical applicability. The conclusion highlights the potential for future research directions, including the exploration of advanced fusion strategies and the extension of AFF to other machine learning paradigms.

Keywords: Deep learning; Advancements; Techniques; Artificial intelligence.

1. Introduction

Deep learning models, a subset of machine learning techniques, have revolutionized numerous fields by yielding state-of-the-art results in tasks such as image classification, natural language processing, and speech recognition. These models, which are primarily based on artificial neural networks, rely on the automatic extraction of hierarchical feature representations from raw data. The learned features are subsequently used to make predictions or decisions based on the input data. The process of combining these features, known as feature fusion, plays a crucial role in determining the effectiveness of deep learning models.

Feature fusion techniques in deep learning are pivotal to the success of these models as they enable the combination of diverse features extracted from multiple layers or sources to produce more informative and discriminative representations. Traditional feature fusion techniques, such as concatenation, element-wise addition, and multiplication, have been extensively utilized in various deep learning architectures. However, these methods often lack the ability to adapt to the specific characteristics of the data and the model, resulting in suboptimal performance and reduced generalization capabilities.

To address these limitations, this paper proposes an Adaptive Feature Fusion (AFF) framework designed to enhance the generalization capabilities of deep learning models by dynamically adapting the fusion process based on the underlying data and model requirements. The central idea of AFF is to leverage a combination of data-driven and model-based fusion strategies to adaptively fuse features in a way that optimizes the model's performance. The proposed framework is both versatile and scalable, allowing for seamless integration with existing deep learning architectures and enabling improvements in performance across a wide range of tasks and applications.

The paper is structured as follows:

- Chapter 2 provides a comprehensive review of the literature on feature fusion in machine learning, tracing its evolution from early techniques to recent advancements.





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- Chapter 3 presents a detailed description of the AFF framework, outlining its key components and the process of designing and implementing fusion layers for various deep learning architectures.
- Chapter 4 describes the experimental setup, including the datasets and performance metrics used to evaluate the efficacy of the proposed approach.
- Chapter 5 presents the results of the experiments, highlighting the performance improvements achieved by the AFF framework compared to traditional feature fusion techniques. A comparative analysis of the results provides insights into the factors contributing to the superior performance of AFF.
- Chapter 6 discusses various realworld applications and use cases where the proposed framework can be employed, demonstrating its practical applicability and potential for widespread adoption.
- Chapter 7 concludes the paper by summarizing the main contributions and outlining possible avenues for future research. These include the exploration of advanced fusion strategies, the extension of the AFF framework to other machine learning paradigms, and the investigation of methods for adaptive feature selection and extraction.

By introducing the Adaptive Feature Fusion framework, this paper aims to advance the state of the art in deep learning by addressing the limitations of traditional feature fusion techniques and enhancing the generalization capabilities of these models. The proposed approach represents a significant step forward in the quest for more robust, adaptable, and effective deep learning models that can meet the diverse and complex challenges of real-world applications [1-3].

2. Literature Review

The Evolution of Feature Fusion in Machine Learning:

2.1. Early Feature Fusion Techniques

Feature fusion, also known as feature combination or feature integration, has been an integral part of machine learning research since its early days. In the context of traditional machine learning algorithms, feature fusion techniques were employed to combine multiple features or feature sets, often extracted from different data sources, to improve the performance of classifiers and regressors. Early feature fusion methods primarily consisted of simple concatenation, averaging, and weighted linear combinations. These methods were widely adopted due to their ease of implementation and computational efficiency.

2.2. Feature Fusion in Shallow Models

As machine learning techniques evolved, researchers began exploring more sophisticated feature fusion strategies. In the realm of shallow models, kernel-based fusion methods gained popularity. These techniques, such as Kernel Principal Component Analysis (KPCA) and Support Vector Machines (SVMs) with multiple kernels, allowed for the fusion of features in a nonlinear space, enabling the learning of complex relationships between features. Another significant development during this period was the emergence of ensemble methods, such as bagging and boosting, which leveraged multiple base learners and combined their outputs to produce a more accurate prediction.





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2.3. Deep Learning and Hierarchical Feature Fusion

The advent of deep learning sparked a paradigm shift in feature fusion techniques. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), were capable of learning hierarchical feature representations from raw data. This led to the exploration of hierarchical feature fusion techniques, which combined features from different layers of the network. Examples of such techniques include skip connections, as seen in Residual Networks (ResNets), and multi-scale feature fusion strategies, as demonstrated in Feature Pyramid Networks (FPNs) and U-Nets.

2.4. Attention-based Feature Fusion

Recent advancements in deep learning have given rise to attention based feature fusion techniques. These methods leverage attention mechanisms, which allow models to selectively focus on relevant features while suppressing less important ones. Attention-based fusion techniques have demonstrated remarkable success in a variety of domains, including image captioning, machine translation, and visual question answering. Examples of attention-based feature fusion models include the Transformer architecture, which introduced self-attention and multi-head attention mechanisms, and the Squeeze-and-Excitation (SE) block, which adaptively recalibrates channel-wise feature responses.

2.5. Graph-based Feature Fusion

Graph-based feature fusion techniques have emerged as a promising approach for handling structured data and irregularly sampled inputs. Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) are prime examples of models that incorporate graph-based fusion methods. These techniques enable the aggregation of features from neighbouring nodes in a graph, allowing for the extraction of meaningful information from complex relational structures.

2.6. Meta-Learning for Feature Fusion

The concept of meta-learning, or learning to learn, has been applied to the problem of feature fusion in recent years. Meta-learning based feature fusion techniques focus on learning optimal fusion strategies given a set of training tasks or scenarios. By incorporating knowledge transfer and adaptation, these methods can generalize to new tasks, enabling the discovery of more effective feature fusion strategies.

In summary, the evolution of feature fusion in machine learning has witnessed a continuous progression from simple linear techniques to more advanced, nonlinear, and adaptive methods [4]. The development of deep learning models and the introduction of attention mechanisms, graph-based techniques, and meta-learning have significantly expanded the capabilities of feature fusion, enabling the extraction of more meaningful and discriminative representations from data [5]. However, despite these advancements, there remains ample room for improvement and innovation, as evidenced by the limitations of existing methods in terms of adaptability and generalization [6].





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3. The Adaptive Feature Fusion(AFF) Framework

The Adaptive Feature Fusion (AFF) framework is designed to address the limitations of traditional feature fusion techniques by dynamically adapting the fusion process according to the underlying data characteristics and model requirements. The central premise of AFF is to combine the strengths of data-driven and model-based fusion strategies, leading to more effective and discriminative feature representations. This section provides an overview of the key components and mechanisms of the AFF framework.

At the core of the AFF framework is the adaptive fusion layer, a specialized layer that can be seamlessly integrated into existing deep learning architectures. The adaptive fusion layer receives features from multiple sources, such as different layers of a neural network, and combines them using a combination of data-driven and model-based strategies. Data-driven strategies, such as attention based mechanisms and graph-based techniques, are utilized to learn the optimal fusion weights based on the input features and their relationships. Model-based strategies, on the other hand, rely on the internal structure of the model and the task at hand to guide the fusion process.

The fusion process in the adaptive fusion layer is governed by a set of fusion functions, which can be linear, nonlinear, or a combination thereof. These functions are learned during the training process, enabling the model to adapt to the specific characteristics of the data and the task. Additionally, the adaptive fusion layer incorporates a meta-learning component that allows it to learn how to optimally combine the outputs of the fusion functions for a given task or scenario. This meta-learning component further enhances the adaptability and generalization capabilities of the AFF framework.

To ensure scalability and versatility, the AFF framework is designed to be compatible with various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Convolutional Networks (GCNs). This compatibility is achieved through the use of modular fusion blocks that can be added to different layers or components of the network, enabling the adaptive fusion of features at multiple scales and levels of abstraction.

The AFF framework also incorporates a set of regularization techniques to prevent overfitting and improve generalization. These techniques include the use of dropout, weight decay, and the introduction of auxiliary tasks that encourage the model to learn more robust and discriminative feature representations [7,8].

In conclusion, the Adaptive Feature Fusion framework represents a novel approach to feature fusion in deep learning models, combining the strengths of data-driven and model-based fusion strategies to achieve improved performance and generalization capabilities. By incorporating adaptive fusion layers into existing architectures [9], the AFF framework enables the development of more robust, adaptable, and effective deep learning models that can better address the diverse and complex challenges of real-world applications.

4. Designing and Implementing Fusion Layers for Deep Learning Architectures

The integration of adaptive fusion layers into existing deep learning architectures is a crucial aspect of the





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Adaptive Feature Fusion (AFF) framework. This section discusses the design and implementation process of fusion layers for various deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Convolutional Networks (GCNs).

To design a fusion layer, the first step is to identify the appropriate sources of features within the architecture. These sources can be different layers or components of the network, such as convolutional layers in CNNs, hidden states in RNNs, or graph convolutions in GCNs. The choice of feature sources depends on the specific architecture and the desired level of abstraction for the fused features.

Once the feature sources have been identified, a fusion block is designed to combine the input features from these sources. The fusion block consists of a set of fusion functions, which can be linear, nonlinear, or a combination thereof. These functions are responsible for transforming the input features into a common representation space, where they can be adaptively combined. The choice of fusion functions depends on the nature of the input features, the desired level of expressiveness, and the computational complexity of the fusion process.

The fusion block also incorporates attention mechanisms and graph-based techniques to learn the optimal fusion weights based on the input features and their relationships. Attention mechanisms allow the model to selectively focus on relevant features while suppressing less important ones, while graph-based techniques enable the aggregation of features from neighboring nodes in a graph structure, capturing complex relational information.

The fusion block is connected to a meta-learning component, which is responsible for learning how to optimally combine the outputs of the fusion functions for a given task or scenario. This component is trained using a set of auxiliary tasks that encourage the model to learn more robust and discriminative feature representations, leading to improved generalization capabilities.

Once the fusion block and meta-learning component have been designed, they are integrated into the deep learning architecture as a new adaptive fusion layer. This layer can be added to different parts of the network, enabling the adaptive fusion of features at multiple scales and levels of abstraction. The integration process is designed to be seamless and modular, ensuring compatibility with a wide range of deep learning models.

Finally, the modified architecture, now equipped with the adaptive fusion layer, is trained using the standard backpropagation algorithm. During training, the fusion functions, attention mechanisms, and meta-learning component are updated alongside the rest of the model, enabling the adaptive fusion process to adapt to the specific characteristics of the data and the task [10].

In summary, the design and implementation of fusion layers for deep learning architectures involve identifying feature sources, designing fusion blocks, incorporating attention mechanisms and graph-based techniques, integrating meta-learning components, and seamlessly adding adaptive fusion layers to the network. Through this process, the AFF framework enables the development of more robust, adaptable, and effective deep learning models that can better address the diverse and complex challenges of real-world applications [11, 12].





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5. Experimentation and Evaluation: Datasets and Performance Metrics

To validate the effectiveness of the Adaptive Feature Fusion (AFF) framework and assess its impact on the performance and generalization capabilities of deep learning models, a series of experiments were conducted. This section provides an overview of the datasets and performance metrics employed in the experimentation and evaluation process [13-15].

5.1. Datasets

The experiments were carried out on multiple benchmark datasets spanning various domains and applications to ensure a comprehensive evaluation. The selected datasets include:

- **Image Classification:** CIFAR-10 and CIFAR-100 are widely used image classification datasets, each consisting of 60,000 32x32 color images, divided into 10 and 100 classes, respectively. These datasets are commonly used to evaluate the performance of deep learning models on fine-grained recognition tasks.
- **Object Detection:** The PASCAL VOC and MS COCO datasets are popular object detection benchmarks that comprise annotated images with multiple object instances and classes. These datasets allow for the assessment of the AFF framework's effectiveness in handling complex scenes and improving localization and recognition capabilities.
- **Sentiment Analysis:** The IMDb dataset contains movie reviews labeled as positive or negative, providing a basis for evaluating the performance of the AFF framework in natural language processing tasks, particularly sentiment analysis.
- **Graph Classification:** The MUTAG and PROTEINS datasets consist of labeled graphs representing chemical compounds and protein structures, respectively. These datasets enable the evaluation of the AFF framework in graph-based tasks and its ability to extract meaningful information from structured data.

5.2. Performance Metrics

To assess the performance of the AFF framework, several metrics were employed across the various tasks and domains:

- **Image Classification and Object Detection:** For these tasks, standard performance metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU) were used. These metrics provide a comprehensive evaluation of the model's classification and localization capabilities.
- **Sentiment Analysis:** In this domain, the performance of the AFF framework was evaluated using accuracy, precision, recall, and F1-score, which are commonly used to measure the effectiveness of text classification models.
- **Graph Classification:** For graph-based tasks, accuracy, and macro-F1 scores were employed as performance metrics. These metrics capture the model's ability to correctly classify graphs and account for class imbalances in the datasets.
- The experiments were designed to provide a thorough evaluation of the AFF framework's impact on the performance and generalization capabilities of deep learning models across various tasks and domains. By using multiple benchmark datasets and performance metrics, the experiments aimed to demonstrate the





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versatility and effectiveness of the AFF framework, as well as its potential for widespread adoption in real-world applications.

6. Comparative Analysis: Adaptive vs. Traditional Feature Fusion Techniques

To demonstrate the advantages of the Adaptive Feature Fusion (AFF) framework over traditional feature fusion techniques, a comparative analysis was conducted. This chapter presents the results of this analysis, highlighting the performance improvements achieved by AFF compared to conventional methods such as concatenation, element-wise addition, and multiplication.

6.1. Image Classification

In the image classification task, experiments were conducted on the CIFAR-10 and CIFAR-100 datasets. The AFF framework was integrated into a baseline Convolutional Neural Network (CNN) architecture, and its performance was compared with the baseline model using traditional feature fusion techniques. The results indicated that the AFF framework consistently outperformed the traditional methods, achieving higher classification accuracy and more discriminative feature representations [16].

6.2. Object Detection

For object detection tasks, experiments were carried out on the PASCAL VOC and MS COCO datasets. The AFF framework was incorporated into a state-of-the-art object detection model, and its performance was compared with the same model using conventional feature fusion techniques. The AFF framework demonstrated superior performance, with improvements in metrics such as precision, recall, F1-score, and Intersection over Union (IoU). This indicates that the AFF framework can effectively enhance the localization and recognition capabilities of object detection models [17].

6.3. Sentiment Analysis

In the sentiment analysis task, experiments were performed on the IMDb dataset. The AFF framework was integrated into a baseline Recurrent Neural Network (RNN) architecture and compared with the baseline model using traditional feature fusion methods. The results showed that the AFF framework achieved higher accuracy, precision, recall, and F1-score compared to the traditional techniques, highlighting its effectiveness in natural language processing tasks [18].

6.4. Graph Classification

For graph classification tasks, experiments were conducted on the MUTAG and PROTEINS datasets. The AFF framework was incorporated into a Graph Convolutional Network (GCN) model and compared with the same model using conventional feature fusion techniques. The AFF framework outperformed the traditional methods, achieving higher accuracy and macro-F1 scores, demonstrating its ability to extract meaningful information from structured data.





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Across all tasks and domains, the AFF framework consistently achieved better performance than traditional feature fusion techniques. The improvements can be attributed to several factors:

- **Adaptive Fusion:** The AFF framework dynamically adapts the fusion process based on the input data characteristics and model requirements, leading to more effective and discriminative feature representations.
- **Data-Driven and Model-Based Strategies:** The combination of data-driven and model-based fusion strategies enables the AFF framework to leverage the strengths of both approaches, resulting in more robust and adaptable models.
- **Meta-Learning:** The meta-learning component of the AFF framework allows it to learn optimal fusion strategies for a given task or scenario, further enhancing its generalization capabilities.

In conclusion, the comparative analysis demonstrates the superiority of the Adaptive Feature Fusion framework over traditional feature fusion techniques. By addressing the limitations of conventional methods, the AFF framework provides a more robust, adaptable, and effective solution for enhancing the performance and generalization capabilities of deep learning models across a wide range of tasks and applications.

7. Conclusion

In this paper, we presented the Adaptive Feature Fusion (AFF) framework, a novel approach to feature fusion in deep learning models that combines the strengths of data-driven and model-based fusion strategies. The AFF framework dynamically adapts the fusion process based on the input data characteristics and model requirements, resulting in more effective and discriminative feature representations. Through a series of experiments and comparative analyses, we demonstrated that the AFF framework consistently outperforms traditional feature fusion techniques across various tasks and domains, including image classification, object detection, sentiment analysis, and graph classification.

The integration of adaptive fusion layers into existing deep learning architectures, coupled with the use of attention mechanisms, graph-based techniques, and meta-learning components, enables the development of more robust, adaptable, and effective deep learning models. The AFF framework has the potential to significantly impact real-world applications, addressing diverse and complex challenges in fields such as computer vision, natural language processing, and graph-based learning.

Despite the promising results achieved by the AFF framework, there are several avenues for future work:

- **Fusion Function Exploration:** In this paper, we utilized linear and nonlinear fusion functions to combine features within the adaptive fusion layer. Future work could investigate alternative fusion functions, such as kernel-based methods or more complex transformations, to further enhance the expressiveness and adaptability of the framework.
- **Hierarchical Fusion:** The AFF framework can be extended to incorporate hierarchical fusion strategies, where features are adaptively combined at multiple levels of abstraction within the deep learning model. This could allow for more granular control over the fusion process and potentially yield even better performance.
- **Transfer Learning and Domain Adaptation:** The current implementation of the AFF framework focuses on





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single-domain tasks. Future research could explore the use of the AFF framework in transfer learning and domain adaptation scenarios, where the goal is to leverage knowledge from one domain to improve performance in another.

- Integration with Emerging Architectures: The AFF framework can be adapted to work with emerging deep learning architectures, such as transformers, capsule networks, and self-supervised learning models. This would further broaden the applicability and impact of the framework in a rapidly evolving field.

In conclusion, the Adaptive Feature Fusion framework represents a significant advancement in the field of feature fusion for deep learning models. By addressing the limitations of traditional techniques, the AFF framework offers a more robust, adaptable, and effective solution that has the potential to transform a wide range of applications across multiple domains.

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