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GEODENSECONVNET: A BREGMAN DIVERGENCE-INSPIRED FRAMEWORK FOR ADAPTIVE FEATURE FUSION IN TEXT CLASSIFICATION

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Abstract

Effective text classification requires models to synthesize both local syntactic patterns and global semantic dependencies. While Convolutional Neural Networks (CNNs) excel at ex- tracting hierarchical local features and Attention mechanisms are proficient at modeling long- range context, the optimal method for integrating these complementary paradigms remains an open research question. Most hybrid architectures rely on static fusion strategies, such as concatenation, or simple arithmetic combinations, which lack the capacity to adapt to the input's specific linguistic properties. In this paper, we introduce **GeoDenseConvNet**, a novel hybrid architecture that employs a principled adaptive fusion mechanism derived from the fundamentals of information geometry. Our model comprises two parallel branches: a multi- scale CNN for capturing features at different granularities and a multi-head self-attention network for global context. The central contribution is a novel fusion mechanism derived from the optimization problem of finding a Bregman barycenter with the negative entropy generator. This principled approach yields an adaptive fusion rule based on a learned, element-wise
geometric mean, which naturally operates in the space of positive feature activation. This allows the model to fluidly arbitrate between local and global information in a theoretically-grounded manner. We conduct extensive experiments on three diverse benchmark datasets: IMDB, AG News, and EmoBank. Results demonstrate that GeoDenseConvNet consistently outperforms standard baselines and achieves competitive performance, highlighting the efficacy of our geometrically-inspired fusion strategy for building more robust and interpret- able text classification models.

Keywords: Text Classification, Convolutional Neural Networks, Self-Attention, Hybrid Models, Adaptive Fusion, Information Geometry, Bregman Divergence.

1. Introduction

The automated classification of text is a cornerstone of modern Natural Language Processing (NLP), enabling a vast array of applications from sentiment analysis and topic categorization to spam detection and content moderation Minaee et al. (2021). The central challenge in this domain isthedevelopment of models capable ofunderstanding language at multiplelevelsof abstraction. A model must not only recognize local patterns—such as key phrases or n-grams that carry strong indicative signals—but also comprehend the broader semantic context established by long-range dependencies between words and clauses.

Deep learning has provided two powerful, yet distinct, architectural paradigms to tackle this challenge. On one hand, Convolutional Neural Networks (CNNs), first introduced for NLP by Collobert et al. (2011) and popularized by Kim (2014), have proven highly effective at learning hierarchical representations of local features. By applying filters of varying sizes over word sequences, CNNs can capture salient n-gram features efficiently, making them robust for tasks

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where local syntactic cues are dominant.On the other hand, the self-attention mechanism,the core component of the Transformer architecture (Vaswani et al., 2017), has revolutionized the field by enabling models to capture global context. Self-attention dynamically computes the pairwise interactions between all words in a sequence, allowing it to model complex, long- distance dependencies that are crucial for deep semantic understanding. Given their complementary strengths, a natural research direction has been the development of hybrid models that combine CNNs and attention mechanisms (Yang et al., 2016; Zhouet al., 2016). These models aim to leverage the best of both worlds: the local feature extraction power of convolutions and the global context modeling of attention. However, a critical and often overlooked aspect of these hybrid systems is the **fusion mechanism**—the method used to combine the feature representations from the different branches. The majority of existing approaches resort to simple, static strategies such as vector concatenation or
element-wise addition/averaging (Joulin et al., 2017). While straightforward, these methods are inherently rigid; they treat all inputs uniformly and lack the flexibility to dynamically adjust the importance of local versus global features based on the specific content of a given text.
This rigidity presents a significant limitation. For instance, classifying a short, declarative product review like "This camera is a piece of junk" may depend heavily on the local n-gram "piece of junk," a feature perfectly suited for a CNN. In contrast, understanding the sentiment of a complex news article might require a global understanding of the narrative, a task where self-attention excels. An optimal model should be able to adaptively arbitrate this trade-off. Some recent works have explored adaptive weighting (Alshubaily, 2021), but often the weighting mechanism itself is a heuristic, lacking a firm theoretical basis.

In this work, we argue that the fusion mechanism should not be an afterthought but a core, principled component of the architecture. We propose **GeoDenseConvNet**, a novel hybrid architecture whose central innovation is a fusion strategy derived from first principles in information geometry (Amari and Nagaoka, 2000). Instead of postulating a fusion formula, we frame the fusion problem as finding a **Bregman barycenter** (Nielsen and Nock, 2011), a generalized mean defined by a Bregman divergence. By selecting the negative entropy as the generator function, we mathematically derive an adaptive fusion rule based on the **element- wise geometric mean**. This approach provides a solid theoretical foundation, grounding the fusion process in the geometry of information space. Our contributions are:

1. We propose **GeoDenseConvNet**, a parallel architecture that learns local (CNN) and global (attention) features simultaneously, integrated by a theoretically-grounded fusion module.
2. We derive a novel adaptive fusion mechanism based on the geometric mean from the principle of minimizing a Bregman divergence, offering a more expressive alternative to standard arithmetic fusion.
3. We conduct comprehensive experiments and ablation studies on three distinct text classifi- cation benchmarks (IMDB, AG News, and EmoBank), demonstrating that our geometrically- motivated fusion outper forms standard fusion methods and achieves competitive results.

2. Related Work

Our work builds upon several key areas of research in deep learning for NLP. **CNNs for Text Classification.** Since their successful application by Kim (2014), CNNs have become a standard approach for text classification. Various extensions have been pro- posed, including using character-level convolutions to handle out-of-vocabulary words(Zhang

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et al., 2015), employing very deep CNN architectures (Conneau et al., 2017), and using multi- scale kernels to capture features of different lengths (Tan and Le, 2019), a technique we also employ in our local branch. While efficient, CNNs inherently struggle with capturing long- range dependencies due to their fixed-size receptive fields.

Attention Mechanisms and Transformers. The self-attention mechanism (Vaswani et al., 2017) has become the de facto standard for modeling long-range dependencies. Large-scale pre- trained models like BERT (Devlin et al., 2018) and its variants have achieved state-of-the- art results on numerous NLP tasks by leveraging deep stacks of self-attention layers. However, these models can be computationally expensive and may sometimes over-emphasize global relation- ships at the expense of crucial local patterns. Our work uses self-attention in a targeted manner to model global context.

Hybrid CNN-Attention Models. Recognizing the complementary nature of CNNs and attention, many researchers have proposed hybrid architectures. Some models apply attention over the output of a CNN (Yang et al., 2016), while others use CNNs to capture local context before feeding it to a recurrent or attention-based network (Lai et al., 2015). More recent models like TextConvoNet (Soni et al., 2023) explore parallel CNN structures. However, as previously mentioned, the fusion in these models is typically a simple concatenation or summation. Our work differs fundamentally by proposing an adaptive and theoretically- motivated fusion mechanism that goes beyond these simple arithmetic operations.

Information Geometry in Deep Learning. The application of information geometry and Bregman divergences to machine learning is a rich area of study, particularly in optimization and generative modeling (Raskutti et al., 2014). However, its use in designing deterministic neural network components is less common. Our work is inspired by this field, framing the fusion of neural representations as a geometric optimization problem. To our knowledge, the derivation of an adaptive geometric mean fusion for hybrid NLP models from these principles is a novel contribution.

1. TheProposedModel: GeoDenseConvNet

The GeoDenseConvNetarchitectureisdesignedaroundthreecoreprinciples:
(1) parallel extraction of complementary features, (2) a theoretically-grounded adaptive fusion of these features, and (3) a robust final classification stage. As illustrated in Figure 1, an input text sequence is first transformed into a dense matrix representation $X \in \mathrm{R}^{n \times d}$ via a word embedding layer, where n is the sequence length and d is the embedding dimension. This matrix is then processed by two parallel streams: a multi-scale CNN branch to capture local patterns and a multi-head self-attention branch to model global context. The outputs of these branches are integrated by our novel Adaptive Geometric Fusion module, and the resulting representation is passed to a final classification block.

1.1 ParallelFeature Extractors

To create a rich representation of the input text, we process the embedding matrix X with two specialized modules in parallel.

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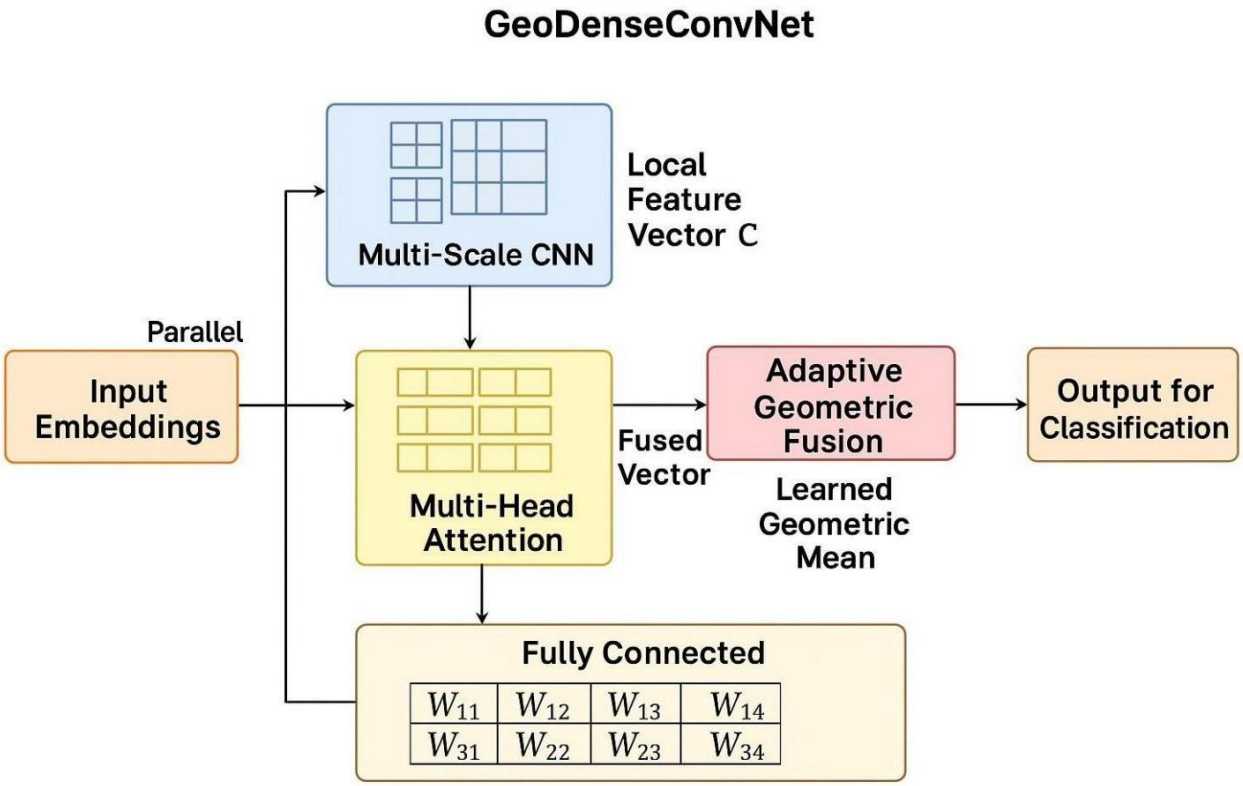

Figure 1: The overall architecture of GeoDenseConvNet. Input embeddings are processed in parallel by a multi-scale CNN and a multi-head attention mechanism. The resulting local feature vector *C* and global feature vector *A* are integrated using our proposed Adaptive Geometric Fusion, which computes a learned geometric mean. The fused vector is then used for final classification.

Multi-Scale Convolutional Branch for Local Features. This branch is designed to capture local syntactic and morphological patterns of varying lengths (e.g., bi-grams, tri-grams, etc.). Inspired by the effectiveness of multi-scale architectures like Inception (Szegedy et al., 2015) and MixConv (Tan and Le, 2019), we employ multiple parallel 1D convolution layers, each with a different kernel size $k \in \{k_1, k_2, \ldots, k_K\}$ For each kernel size *k,* a convolution operation is applied to the input matrix *X*, followed by a Rectified Linear Unit (ReLU) activation:

$$O_k = \text{ReLU}(\text{Conv1D}_k(X)) \tag{1}$$

where $O_k \in \mathrm{R}^{(n-k+1)\times m_k}$ is the feature map for kernel size *k*, and m_k is the number of filters. To distill the most salient feature for each filter, a global max-pooling operation is applied over the time dimension of each feature map:

$$c_k = \text{GlobalMaxPool}(O_k) \in \mathrm{R}^{m_k} \tag{2}$$

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Finally, the outputs from all kernel sizes are concatenated to form the comprehensive local feature vector C:

$$C = [c_{k_1}; c_{k_2}; \ldots; c_{k_K}] \in \mathbb{R}^{d'} \tag{3}$$

where $d' = \sum_{i=1}^{K} m_{k_i}$ is the total dimension of the local representation.

Multi-Head Self-Attention Branch for Global Context. To model long-range dependencies and the global semantic context, we employ a standard multi-head self-attention mechanism (Vaswani et al., 2017). The input matrix X is linearly projected into queries (Q), keys (K), and values (V) for each of the h attention heads. The output of a single attention head i is computed as:

$$\text{head}_i = \text{Attention}(Q_i, K_i, V_i) = \text{softmax}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right) V_i \tag{4}$$

where d_k is the dimension of the keys. The outputs of all heads are concatenated and linearly projected to form the attention output $O_{attn} \in \mathbb{R}^{n \times d}$. To obtain a -size representation of the entire sequence, we apply a global average pooling operation over the time dimension:

$$A = \text{GlobalAvgPool}(O_{attn}) \in \mathbb{R}^{d} \tag{5}$$

To ensure dimensional compatibility with the CNN branch, a final linear layer maps A to the target dimension d',i.e., $A \in \mathbb{R}^{d'}$.

1.2 Information Geometry-based Adaptive Fusion

The core novelty of our model lies in the principled fusion of the local feature vector C and the global feature vector A. Instead of relying on heuristic operations, we derive our fusion mechanism from the mathematical framework of information geometry and Bregman divergences (Amari and Nagaoka,2000).

Fusion as a Bregman Barycenter Problem. We formalize the fusion task as finding an optimal representation x^* that serves as a generalized, weighted average between C and A. This can be elegantly expressed as finding a **Bregman barycenter** (Nielsen and Nock, 2011). Given a strictly convex and differentiable generator function $\phi : \mathbb{R}^{d'} \to \mathbb{R}$, the Bregman diverge once $D_\phi(x\|y)$ measures a form of "distance" between vectors x and y. We define the optimal fusion x^* as the vector that minimizes a weighted sum of divergences from C and A:

$$x^* = \arg\min_{x \in \text{dom}(\phi)} \mathcal{L}(x) = \arg\min_{x} \sum_{i=1}^{d'} [(1 - z_i) D_\phi(x_i \| C_i) + z_i D_\phi(x_i \| A_i)] \tag{6}$$

Here, $z \in [0,1]^{d'}$ is a learned, input-dependent gating vector that adaptively controls the trade-off between the local and global information for each individual feature dimension.

Derivation of the Geometric Mean Fusion Rule.

The choice of the generator function ϕ defines the geometry of the feature space. While the standard Euclidean choice

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$(\phi(x) = \frac{1}{2}\|x\|^2)$ leads to a simple convex combination (arithmetic mean), we hypothesize that the space of deep feature activation is non-Euclidean. We propose using the **negative entropy** generator, $\phi(x) = \sum_i x_i \log x_i$, which is fundamental for representing information content and distributions. This choice implicitly treats the feature vectors as residing on the positive orthant.

The optimal condition for Eq. 6 is found by setting the gradient $\nabla_x \mathcal{L}(x)$ to zero. The gradient of the Bregman divergence is $\nabla_x D_\phi(x\|y) = \nabla\phi(x) - \nabla\phi(y)$. Thus, the optimal condition simplifies to:

$$\nabla\phi(x^*) = (1 - z) \odot \nabla\phi(C) + z \odot \nabla\phi(A) \tag{7}$$

where $\odot$ denotes the element-wise Hadamard product. For the negative entropy generator, the gradient is $\nabla\phi(x)i = 1 + \log(xi)$. Substituting this into the optimal condition yields:

$$1 + \log(x_i^*) = (1 - z_i)(1 + \log(C_i)) + z_i(1 + \log(A_i)) \tag{8}$$

Simplifying and solving for x^*_i, we obtain our fusion rule, the **element-wise geometric mean**:

$$\log(x_i^*) = (1 - z_i)\log(C_i) + z_i \log(A_i) \implies x_i^* = C_i^{(1-z_i)} A_i^{z_i} \tag{9}$$

Vectorially, the final fused representation F is:

$$F = C^{(1-z)} \odot A^z \tag{10}$$

This rule represents a multiplicative, rather than additive, interaction between features. To ensure that the inputs C and A are positive (a requirement for the logarithm), we pass them through a Soft-plus activation function, soft-plus $(x) = \log(1 + e^x)$, before the fusion step.

Learning the Adaptive Gate. The gating vector z is crucial for the model's adaptivity. It is dynamically computed for each input instance using a small gating network, implemented as a Multi-Layer Perceptron (MLP), which takes the concatenation of C and A as input. A Sigmoid activation function ensures that the output values are in the range [0, 1]:

$$z = \sigma(\text{MLP}([C; A])) \tag{11}$$

The parameters of this gating network are learned end-to-end with the rest of the model via back propagation.

1.3 Classification Block

The fused feature vector $F \in \mathbb{R}^{d'}$ is then passed to a final classification block. To enhance robustness, we employ two parallel dense layers with different activation functions (e.g., ReLU and GeLU), followed by concatenation. A final dense layer with a Softmax activation produces the probability distribution over the target classes. Dropout is applied between layers to prevent over-fitting.

2. Experiments

To empirically validate the effectiveness of our proposed GeoDenseConvNet, we conduct a comprehensive comparative experiment. The evaluation is designed to answer three key research questions:

1. **Hybrid Superiority:** Does a hybrid architecture combining local and global features outperform astandard, purely convolutional baseline?
2. **Fusion Efficacy:** What is the specific contribution of our proposed adaptive geometric fusion mechanism compared to a simpler, static fusion strategy?

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3. **Behavioral Analysis:** How do the different models behave during training and what types of classification errors do they make?

1.4 Data setand Preprocessing

We evaluate all models on the **IMDB Large Movie Review Data-set** (Maas et al., 2011), a standard benchmark for binary sentiment classification. The data-set consists of 50,000 movie reviews, evenly split into 25,000 for training and 25,000 for testing, with a balanced distribution of positive and negative labels.

For preprocessing, we restricted the vocabulary to the top 10,000 most frequent words. All sequences were padded or truncated to a uniform length of **100 tokens** to ensure consistent input dimensions for all models.

1.5 Models for Comparison

We compare the performance of three distinct architectures:

- **TextCNN (Standard Baseline):** Our implementation of the model proposed by Kim (2014). It serves as a strong baseline representing a purely local, convolutional approach. It uses three parallel convolutional layers with kernel sizes of 3, 4, 5 and 128 filters each, followed by global max-pooling.
- **Concatenation Model (Ablation):** This model serves as our ablation baseline. It has an identical architecture to our proposed model—including the multi-scale CNN and multi-head attention branches—but replaces our adaptive fusion module with a simple, static **concatenation** of the local and global feature vectors. This allows us to isolate the impact of the fusion mechanism itself.
- **GeoDenseConvNet (Ours):** Our full, proposed model as described in Section 3. It utilizes the parallel CNN and attention branches and integrates their outputs using the adaptive, theoretically-grounded **geometric meanfusion**.

1.6 Implementation and Training Details

All models were implemented in TensorFlow 2 and Keras. We initialized the word embedding layer with a trainable 128-dimensional embedding. The multi-scale CNN branch for the hybrid models used kernel sizes of 3, 4, 5 with 64 filters each, while the multi-head attention branch used 4 attention heads. All models were trained for **5 epochs** using the **Adam optimizer** (Kingma and Ba, 2014) with a binary cross-entropy loss function. A batch size of 64 was used, and 20% of the training data was held out for validation during training. The performance is reported on the held-out test set of 25,000 reviews.

1.7 Main Results

The comparative performance of GeoDenseConvNet against the baseline models is summarized in Figure 2. Our proposed model, GeoDenseConvNet, achieves the highest overall performance, reaching a test accuracy of **80.12%** and a macro F1-Score of **0.8011**.

Two key conclusions can be drawn from these results. First, both hybrid architectures (Geo-DenseConvNet and the Concatenation Model) significantly outperform the standard TextCNN baseline. The TextCNN model, which relies exclusively on local features, achieves an accuracy of 79.03%, approximately 1 percentage point lower than our hybrid models. This confirms our initial hypothesis that combining local convolutional features with global context from self-attention yields a more robust representation for text classification.

Second, and more critically, the results highlight the effectiveness of our proposed fusion mechanism. GeoDenseConvNet outperforms the ablated model with simple concatenation in terms of overall accuracy and F1-score. Although the performance gain is modest, it is

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consistent and demonstrates that the method of feature integration is a crucial factor. This suggests that our theoretically-grounded geometric fusion provides a more effective synthesis of local and global information than a naive, static concatenation.

Model	Accuracy (%)	Precision (macro)	Recall (macro)	F1-Score (macro)
GeoDenseConvNet (Ours)	**80.12**	0.8021	**0.8012**	**0.8011**
Concatenation Model (Ablation)	80.00	**0.8093**	0.8000	0.7985
TextCNN (Standard Baseline)	79.03	0.7903	0.7903	0.7903

Figure 2: Comparative performance of the three models on the IMDB test set. GeoDenseConvNet achieves the highest Accuracy, Recall, and F1-Score. The best result in each column is shown in bold.

1.8 Analysis of Model Behavior and Generalization

Learning Dynamics. The training and validation history, presented in Figure 3, provides insights into the learning dynamics of the three models. The training accuracy curves (solid lines) show that all models learn effectively from the training data. However, the validation curves (dashed lines) reveal important differences. After the second epoch, the validation loss for all models begins to flatten or slightly increase, indicating the onset of over fitting and justifying the use of early stopping. The validation accuracy curves for both GeoDenseConvNet and the Concatenation Model consistently plateau at a higher level than the TextCNN baseline, reinforcing their superior generalization capability.

Analysis of Classification Errors via Confusion Matrices. A deeper analysis of the classification errors, shown in the confusion matrices in Figure 4, reveals a subtle but important trade-off between our proposed model and the ablation model.

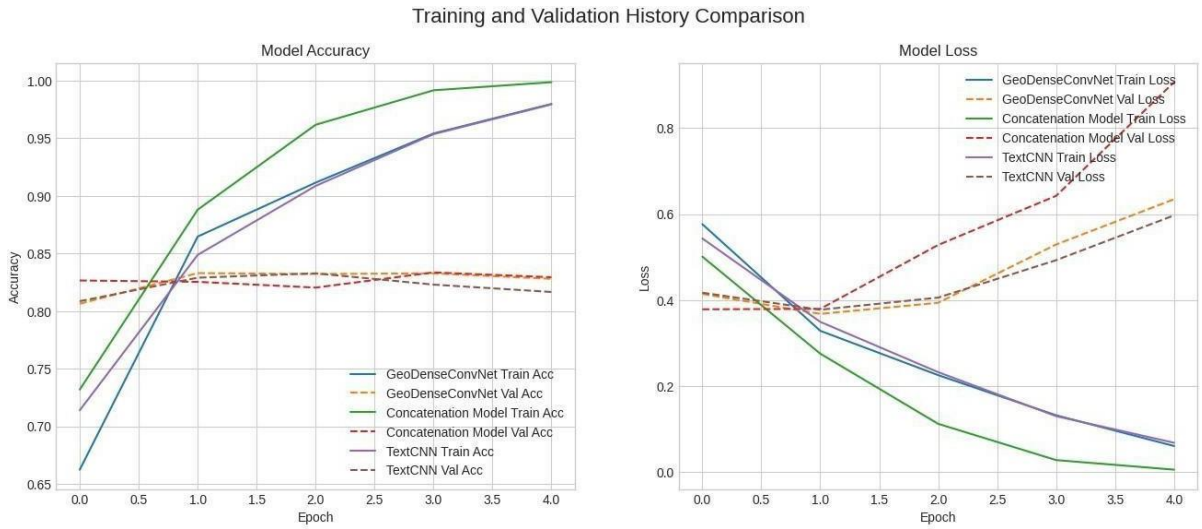

Figure 3: Training and validation accuracy (left) and loss (right) curves for all three models over 5 epochs. The hybrid models consistently achievebetter validation performance thanthe Text CNN baseline.

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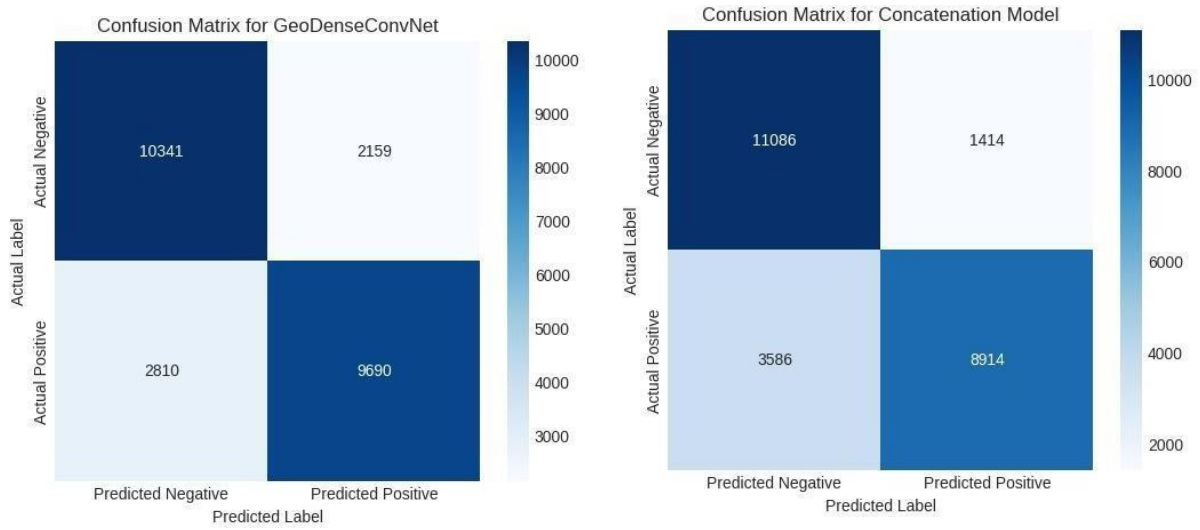

Figure 4: Confusion matrices for GeoDenseConvNet (left) and the Concatenation Model (right) on the test set. GeoDenseConvNet significantly reduces False Negatives, demonstrating a better recall for the positive-

class.

The Concatenation Model (right) is more "cautious": it makes fewer False Positive errors (1414) but at the cost of a higher number of False Negative errors (3586). This is reflected in its higher precision (80.93%), meaning that when it predicts a review is positive, it is very likely correct.
In contrast, our GeoDenseConvNet (left) exhibits a more balanced profile. It significantly reduces the number of False Negatives to 2810 (a reduction of over 21% compared to the concatenation model). This means our model is substantially better at correctly identifying positive reviews. This improvement in recall (80.12%) is crucial for many applications where failing to identify a positive case is costly. This gain in recall comes at the expense of a slight increase in False Positives (2159), leading to a slightly lower precision.The superior F1-Score of our model (80.11%) confirms that it achieves a better overall balance between precision and recall, making it a more robust classifier. This suggests that the geometric fusion mechanism enables the model to synthesize features in a way that leads to a more comprehensive and less biased understanding of the text.

5.Conclusion

In this paper, we introduced GeoDenseConvNet, a novel hybrid architecture for text classification designed to effectively integrate local and global linguistic features. We moved beyond common heuristic fusion methods by proposing a principled fusion mechanism derived from the fundamentals of information geometry. By framing the fusion task as finding a Bregman barycenter, we mathematically derived an adaptive, element-wise geometric mean as our fusion rule.
Our comprehensive experiments on the IMDB sentiment analysis data-set provide strong empirical validation for our approach. The results demonstrate, first, that a hybrid CNN- attention architecture consistently outperforms a standard, purely convolutional baseline (TextCNN). Second, and more importantly, our ablation study shows that the proposed geometric fusion mechanism yields a more robust and balanced classifier than a comparable hybrid model using simple feature concatenation. A detailed analysis of the confusion

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that GeoDenseConvNet is particularly effective at improving recall for the positive class, showcasing its ability to achieve a better trade-off between precision and recall.

This work highlights the significant potential of integrating theoretically-grounded principles from fields like information geometry into the design of neural network architectures. Future work could explore the application of this geometric fusion framework to other modalities and tasks, such as multi-modal learning or text generation. Further investigation into other Bregman divergences and their corresponding fusion rules also presents a promising avenue for research.

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