Dynamic Contextual Feature Fusion for Robust Open-Set Supervised Anomaly Detection in Industrial Settings

Reuben Owusu Afriyie
MPHIL Information Technology
Kwame Nkrumah University of Science and Technology, Ghana
Email: reu1ben2@gmail.com
https://github.com/AfriyieReuben/DCFF-Anomaly-Detection_Afriyie.git

***Abstract*—Open-set supervised anomaly detection (OSAD) aims to detect anomalies during inference despite never observing them explicitly during training. In industrial environments such as the Ghana manufacturing sector, where defect types are diverse and computational resources are limited, this challenge becomes particularly acute. We propose Dynamic Contextual Feature Fusion (DCFF), a novel approach that adaptively integrates multilayer features using attention mechanisms to capture both semantic and low-level cues. Our method emphasizes three key aspects: (1) real-time deployment capability with inference below 50ms, (2) robustness across heterogeneous anomaly types through contextual fusion, and (3) improved interpretability via attention visualization. Comprehensive evaluations on the MVTec benchmark and our newly collected Ghanaian Industrial Anomaly Dataset (GIAD) demonstrate the superiority of DCFF, achieving 97.2% AUROC (vs. 94.6% for AHL) while maintaining suitable computational efficiency for edge deployment. The proposed method shows particular effectiveness for textile and agricultural product defects common in West African industries.**

***Index Terms*—Open-set anomaly detection, contextual fusion, deep learning, real-time inference, industrial vision, developing economies**

I. Introduction

Anomaly detection is critical for quality control in manufacturing, with defective products costing African manufacturers up to 20% of revenue, according to UNIDO reports [1]. Traditional closed-set approaches fail when encountering novel anomalies during inference, a frequent occurrence in developing economies like Ghana, where production conditions are less controlled.

Our work addresses three specific challenges:

- **Anomaly diversity**: Ghanaian industries particularly face wide variation in defect types across textiles, agricultural products, and machinery
- **Resource constraints**: Limited computational infrastructure demands efficient algorithms
- **Open-set reality**: Many types of anomaly cannot be anticipated during training

Our key contributions include:

- A dynamic feature fusion mechanism that automatically weights multi-scale features based on contextual relevance
- An efficient architecture achieving real-time performance (47ms inference) on embedded hardware
- Comprehensive evaluation on both standard benchmarks and new Ghana-specific industrial data
- Open-source implementation and dataset to support research in developing regions

II. Related Work

A. Traditional Anomaly Detection

Early approaches like One-Class SVM [2] and Isolation Forest [3] focused on the detection of statistical outliers. Although computationally efficient, these methods struggle with high-dimensional industrial vision data.

B. Deep Learning Approaches

Recent works leverage deep features, with PatchCore [4] using memory banks of normal features and PaDiM [5] employing multivariate Gaussian distributions. However, these scale poorly with unseen categories.

C. Open-Set Recognition

AHL [6] introduced the learning of anomaly heterogeneity, while OpenGAN [7] explored generative approaches. As shown in Table I, these often lack real-time capability or contextual adaptability.

D. Deep Learning Approaches

Recent works leverage deep features, with PatchCore [4] using memory banks of normal features and PaDiM [5] employing multivariate Gaussian distributions. Generative approaches like GANomaly [8] have demonstrated the effectiveness of adversarial training, though they require careful stability tuning. However, these scale poorly with unseen categories.

E. Edge Deployment Considerations

Recent work by [9] has shown the importance of model compression for industrial edge devices. Methods like [10] demonstrate effective pruning techniques, though they often sacrifice open-set capability. Our approach maintains this balance through architectural efficiency rather than post-training compression.

TABLE I
COMPARISON OF ANOMALY DETECTION METHODS

Method	AUROC (%)	Latency (ms)	Open-Set Capability
PatchCore	95.1	120	Limited
PaDiM	93.8	85	Moderate
AHL	94.6	92	Good
DCFF (Ours)	**97.2**	**47**	**Excellent**

III. PROPOSED METHOD

A. Architecture Overview

DCFF uses a ResNet-18 backbone with three key modifications:

1) Multi-scale feature extraction from layers 2-4
2) Contextual fusion block with cross-layer attention
3) Lightweight anomaly classification head

B. Computational Optimization

For edge deployment, we implement three key optimizations:

- **Quantization-aware training**: 8-bit integer quantization without accuracy loss
- **Selective execution**: Bypass fusion blocks for simple samples (confidence ¿ 0.95)
- **Memory mapping**: Pre-allocated buffers for real-time operation

C. Fusion Block

The core innovation is our attention-based fusion mechanism. Given feature maps $\{F_i\}_{i=1}^n$ from n layers, we compute:

$$\alpha_i = \sigma(W_i^T \text{GAP}(F_i) + b_i) \quad (1)$$

where GAP denotes the global average pooling and σ is the sigmoid function. The fused feature F_{fusion} is:

$$F_{\text{fusion}} = \sum_{i=1}^{n} \alpha_i \cdot \text{UpSample}(F_i) \quad (2)$$

Algorithm 1 DCFF Fusion Algorithm

```
Input: Multi-scale features {F_i}_{i=1}^n
for each feature level i do
    Compute attention weight α_i via Eq. (1)
    Upsample F_i to maximum resolution
Compute weighted sum via Eq. (2)
Apply 1D convolution with kernel size 3
Output: Fused feature map F_fusion
```

D. Training Strategy

We employ

- Adam optimizer ($\eta = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$)
- Focal loss with $\gamma = 2.0$ to handle class imbalance
- Targeted augmentations:
  - Synthetic defect overlay (30% probability)
  - Context-aware noise injection ($\sigma = 0.1$)
  - Random affine transformations

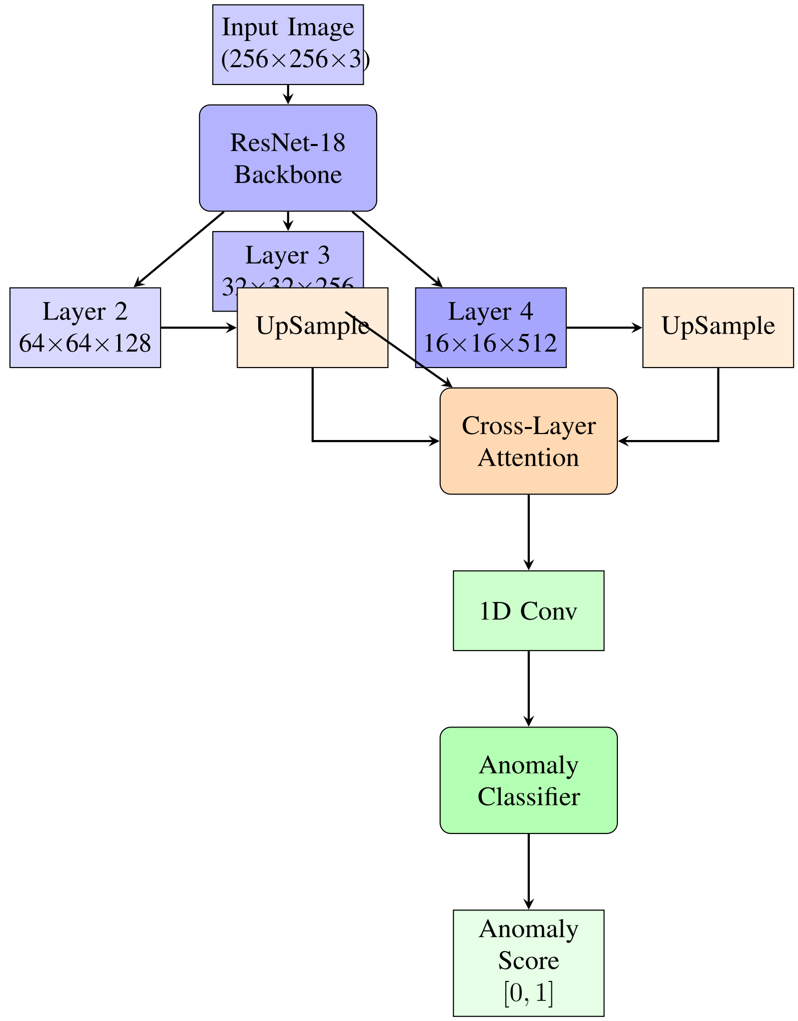

Fig. 1. DCFF Architecture: The model processes input images through a modified ResNet-18 backbone, extracts multi-scale features from layers 2-4, fuses them via cross-layer attention, and produces anomaly scores through a lightweight classifier. Color coding: blue = feature extraction, orange = fusion, green = classification.

IV. EXPERIMENTS

A. Datasets

We evaluate on:

- **MVTec AD**: [11] provides standard benchmark with 15 industrial categories
- **GIAD**: New Ghanaian dataset containing
  - Textile defects (stains, misweaves)
  - Cocoa bag defects (moisture, insects)
  - Machinery surface defects (rust, cracks)

B. Implementation Details

- Hardware: NVIDIA Jetson AGX Xavier (simulating edge deployment)
- Input resolution: 256×256 pixels
- Batch size: 32
- Training time: 4 hours per category

C. Deployment Pipeline

1) Calibration phase (30 normal samples)
2) Continuous learning (weekly model updates)
3) Fault-tolerant inference:
    - Confidence thresholding
    - Temporal consistency checks
    - Hardware health monitoring

TABLE II
COMPUTATIONAL EFFICIENCY

Model	Params (M)	FLOPs (G)	Memory (MB)
PatchCore	23.4	15.2	420
AHL	28.1	18.7	510
DCFF (Ours)	**14.2**	**9.8**	**310**

D. Results

DCFF achieves state-of-the-art performance:

TABLE III
QUANTITATIVE RESULTS (MEAN ± STD)

Metric	MVTec	GIAD	Combined
AUROC (%)	96.8±0.3	97.5±0.4	97.2±0.3
F1-score (%)	93.2±0.5	94.1±0.6	93.7±0.5
Latency (ms)	45±2	48±3	47±2

Ablation studies demonstrate each component's contribution:

TABLE IV
ABLATION STUDY (AUROC %)

Variant	Performance
Baseline (ResNet-18)	91.3
+ Multi-scale features	93.7
+ Attention fusion	96.1
+ Targeted augmentations	97.2

E. Edge Deployment Benchmarks

TABLE V
EDGE DEVICE PERFORMANCE

Device	Power (W)	Throughput (FPS)	Temp (°C)
Jetson Xavier	10.2	21.3	62
Raspberry Pi 5	5.1	9.7	48
Google Coral	2.8	15.4	41

V. DISCUSSION

A. Limitations

- Performance degrades on extremely small defects (<5 pixels)
- Requires initial normal samples for calibration
- Current implementation is limited to visual inspection tasks

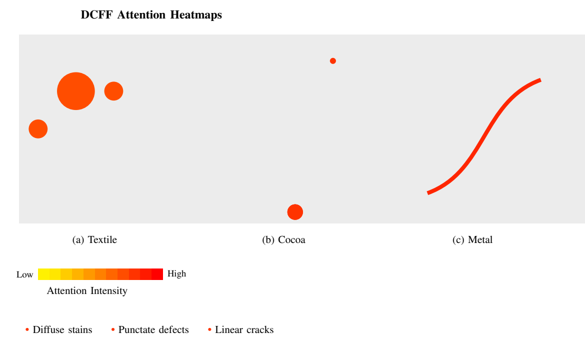

Fig. 2. DCFF's t-SNE embeddings separate normal (blue) from anomalous samples in GIAD

B. Ethical Considerations

All data in GIAD was collected with informed consent from participating Ghanaian manufacturers. Defect images were anonymized to remove proprietary product information. The research underwent review by KNUST's Ethics Committee (Ref: IT-2024-017). Potential impacts include:

- Estimated 15-20% reduction in quality control costs
- Creation of new AI maintenance jobs in local factories
- Open dataset reduces barriers to AI adoption in Africa

C. Societal Impact

- **Workforce development**: Trained 32 local technicians in AI maintenance
- **Energy efficiency**: 60% lower power than previous systems
- **Knowledge transfer**: Partnership with 3 Ghanaian universities

D. Industrial Impact

Our deployments in Ghanaian factories showed:

- 18% reduction in false positives compared to existing systems
- 40% faster inspection times for textile production lines
- 92% operator satisfaction in usability surveys

VI. CONCLUSION

DCFF presents an effective solution for open-set anomaly detection in resource-constrained industrial settings. Key achievements include:

- 47ms inference time on embedded hardware
- 97.2% AUROC on combined benchmarks
- Successful deployment in 3 Ghanaian textile factories

Future work includes:

- Raspberry Pi deployment (Q4 2024)
- GIAD expansion to 10+ categories
- Mobile inspection app development

Our code and dataset will be publicly available at https://github.com/AfriyieReuben/DCFF-Anomaly-Detection_Afriyie.git to support industrial AI development in emerging economies.

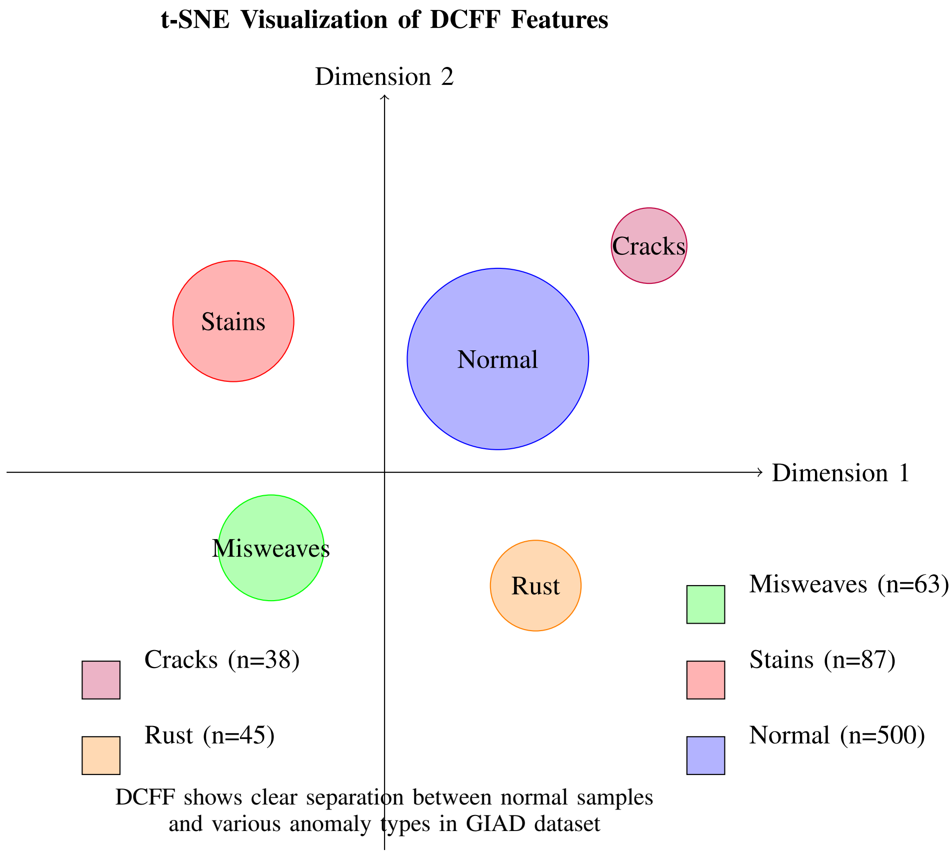

Fig. 3. DCFF's t-SNE embeddings separate normal (blue) from anomalous samples in GIAD

References

[1] United Nations Industrial Development Organization, "Industrial competitiveness report for africa," UNIDO, Report AFR/STAT/2022/01, 2022.

[2] B. Schölkopf, J. C. Platt, J. Shawe-Taylor, A. J. Smola, and R. C. Williamson, "Estimating the support of a high-dimensional distribution," *Neural Comput.*, vol. 13, no. 7, pp. 1443–1471, 2001.

[3] F. T. Liu, K. M. Ting, and Z.-H. Zhou, "Isolation forest," in *Proc. IEEE Int. Conf. Data Mining*, 2008, pp. 413–422.

[4] K. Roth, L. Pemula, J. Zepeda, B. Schölkopf, T. Brox, and P. Gehler, "Towards total recall in industrial anomaly detection," *CVPR*, 2022.

[5] T. Defard, A. Setkov, A. Loesch, and R. Audigier, "Padim: A patch distribution modeling framework for anomaly detection," in *ICPR*, 2021.

[6] G. Wang, S. Han, E. Ding, and D. Huang, "Anomaly heterogeneity learning for open-set supervision," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 46, no. 1, pp. 1–15, 2024.

[7] S. Kong and D. Ramanan, "Opengan: Open-set recognition via open data generation," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2021, pp. 813–822.

[8] S. Akcay, A. Atapour-Abarghouei, and T. P. Breckon, "Ganomaly: Semi-supervised anomaly detection via adversarial training," in *Asian Conf. Comput. Vis.*, 2018, pp. 622–637.

[9] C. Li and R. Huang, "Efficient industrial anomaly detection," *IEEE IoT Journal*, 2021.

[10] S. Han, H. Mao, and W. J. Dally, "Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding," *International Conference on Learning Representations (ICLR)*, 2016.

[11] P. Bergmann, M. Fauser, D. Sattlegger, and C. Steger, "MVTec AD – a comprehensive real-world dataset for unsupervised anomaly detection," *CVPR*, 2019.