

# MedFuse: a multi-source data fusion framework for diabetic retinopathy lesion segmentation

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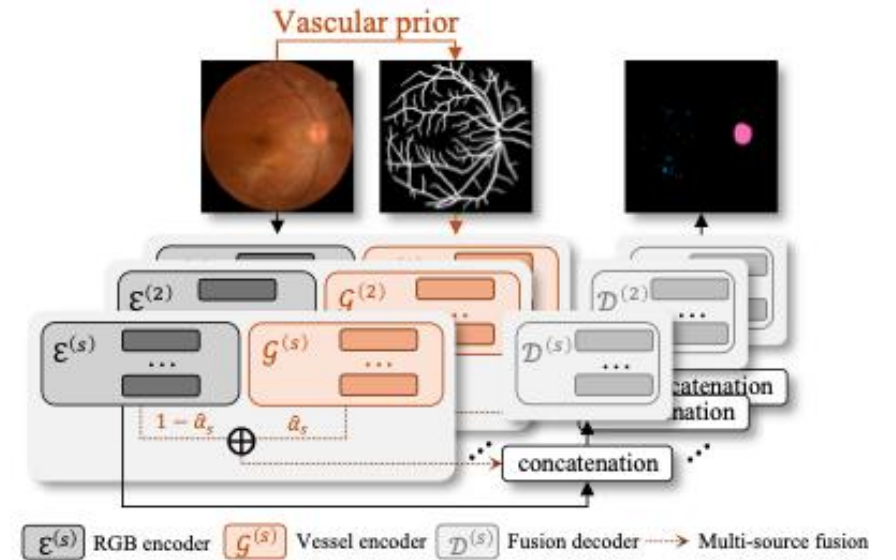
# Problems & Ideas

## Problems of conventional approaches:

- ❑ Existing models rely heavily on texture features (texture-centric).
- ❑ They lack intrinsic anatomical understanding of the retina.
- ❑ High annotation cost of retina imaging.

## Ideas (Our Solution):

- ✓ **Multi-Source Fusion:** A dual-encoder framework to fuse RGB features with structural priors hierarchically.
- ✓ **Mechanism-Guided:** Explicitly integrate the "Vascular Structural Prior" as an anatomical anchor.
- ✓ **LLM-Empowered:** Use Large Language Models for zero-shot generation of vascular maps (annotation-free).



**Vessel-Pred**  
Vessel segmentation model trained on a dataset (e.g., FIVES)

Input: [Image] → [Image] Output

**LLM-Assist**  
You are an expert medical imaging model in DR analysis.

**Requirements:**

1. Identify all visible retinal vessels, including large arteries, veins, and fine capillary branches.
2. The output should represent the likelihood of each pixel belonging to a vessel, as a grayscale probability map (range 0–1).
3. Preserve precise vessel boundaries, continuity, and bifurcations.
4. Ignore non-vascular structures such as the optic disc, macula, artifacts, and background.
5. Ensure that low-contrast or faint vessels are still captured with smooth probability transitions.
6. Do not perform any diagnosis or lesion labeling. Focus strictly on vascular structure extraction.

**Output format:-** Provide a vessel probability map with the same spatial resolution.  
- No textual explanations; return only the probability map.

Input: [Image] → [Image] Output

# Main Contributions & Results

- ✓ Proposed MedFuse, a flexible framework integrating anatomical priors for robust DR segmentation.
- ✓ Introduced a zero-shot, LLM-driven strategy for vascular structure extraction.
- ✓ Achieved consistent performance gains across various backbones.

**Table 1** Quantitative comparison of lesion segmentation performance on the DDR dataset (mean±std). Unit: %.

Model	MedFuse	IoU					AUPR				
		mIoU	EX	HE	SE	MA	mAUPR	EX	HE	SE	MA
PSPNet	–	24.80±0.15	37.31±0.13	26.64±0.17	24.51±0.15	8.75±0.11	38.03±0.19	57.04±0.18	42.32±0.20	42.71±0.15	14.85±0.12
	✓	<b>25.72±0.16</b>	<b>38.63±0.15</b>	<b>27.92±0.17</b>	<b>26.07±0.16</b>	<b>10.24±0.11</b>	<b>40.28±0.18</b>	<b>58.36±0.17</b>	41.95±0.18	<b>44.06±0.14</b>	<b>16.12±0.13</b>
Deeplabv3+	–	26.15±0.17	40.12±0.14	24.86±0.16	24.48±0.18	15.11±0.11	43.96±0.20	61.46±0.18	52.13±0.16	38.89±0.13	28.33±0.12
	✓	<b>27.18±0.16</b>	<b>41.71±0.15</b>	<b>26.34±0.18</b>	<b>25.94±0.16</b>	<b>16.73±0.13</b>	<b>44.79±0.19</b>	<b>62.63±0.19</b>	<b>53.62±0.15</b>	<b>40.34±0.13</b>	<b>29.64±0.13</b>
Twins-SVT	–	29.27±0.17	39.70±0.14	36.24±0.15	29.08±0.15	12.07±0.10	46.08±0.17	59.71±0.15	52.72±0.17	49.96±0.14	21.54±0.12
	✓	<b>30.23±0.16</b>	<b>40.63±0.16</b>	<b>37.13±0.14</b>	<b>30.12±0.14</b>	<b>13.02±0.10</b>	<b>47.01±0.16</b>	<b>60.64±0.14</b>	<b>53.64±0.16</b>	<b>50.93±0.13</b>	<b>22.33±0.11</b>
UNet	–	25.69±0.15	36.68±0.13	23.79±0.16	<b>28.47±0.16</b>	13.83±0.11	39.13±0.16	60.31±0.17	<b>37.25±0.18</b>	40.92±0.14	17.36±0.11
	✓	<b>26.26±0.15</b>	<b>37.72±0.15</b>	<b>24.79±0.16</b>	28.23±0.15	<b>14.30±0.11</b>	<b>39.95±0.17</b>	<b>61.48±0.16</b>	36.53±0.15	<b>41.33±0.14</b>	<b>18.20±0.10</b>
Swin-L	–	30.31±0.17	41.17±0.15	30.79±0.14	35.81±0.17	13.48±0.12	47.47±0.16	63.10±0.15	51.35±0.15	52.99±0.13	24.46±0.11
	✓	<b>31.64±0.16</b>	<b>42.53±0.16</b>	<b>32.05±0.15</b>	<b>37.23±0.16</b>	<b>14.86±0.12</b>	<b>48.15±0.17</b>	<b>64.25±0.16</b>	<b>52.56±0.15</b>	<b>54.46±0.14</b>	<b>25.84±0.12</b>

**Table 2** Quantitative comparison of lesion segmentation performance on the IDRiD dataset (mean±std). Unit: %.

Model	MedFuse	IoU					AUPR				
		mIoU	EX	HE	SE	MA	mAUPR	EX	HE	SE	MA
PSPNet	–	41.83±0.21	57.52±0.19	<b>45.61±0.27</b>	43.87±0.30	19.24±0.33	58.64±0.21	75.03±0.23	<b>63.47±0.25</b>	63.38±0.29	32.42±0.31
	✓	<b>43.28±0.19</b>	<b>59.87±0.17</b>	45.58±0.22	<b>46.15±0.26</b>	<b>21.08±0.31</b>	<b>59.97±0.17</b>	<b>76.38±0.19</b>	63.29±0.25	<b>63.91±0.27</b>	<b>34.71±0.27</b>
Deeplabv3+	–	45.02±0.19	66.08±0.20	44.62±0.24	44.72±0.28	25.43±0.33	63.70±0.18	82.04±0.22	63.23±0.26	<b>64.52±0.28</b>	43.05±0.28
	✓	<b>46.91±0.17</b>	<b>67.27±0.18</b>	<b>45.82±0.24</b>	<b>45.18±0.24</b>	<b>29.18±0.29</b>	<b>64.96±0.18</b>	<b>83.08±0.21</b>	<b>64.07±0.22</b>	64.41±0.27	<b>46.28±0.26</b>
Twins-SVT	–	47.60±0.18	64.72±0.19	51.79±0.25	44.97±0.25	27.04±0.29	63.90±0.17	80.12±0.21	<b>68.87±0.25</b>	63.22±0.26	43.28±0.28
	✓	<b>48.39±0.16</b>	<b>66.19±0.17</b>	<b>51.96±0.23</b>	<b>46.16±0.25</b>	<b>29.25±0.27</b>	<b>65.07±0.15</b>	<b>81.09±0.18</b>	68.85±0.23	<b>64.12±0.23</b>	<b>45.47±0.25</b>
UNet	–	44.60±0.22	60.23±0.21	47.85±0.27	47.76±0.29	<b>22.36±0.34</b>	56.82±0.21	64.21±0.22	64.08±0.28	63.99±0.28	35.01±0.31
	✓	<b>46.86±0.19</b>	<b>61.12±0.19</b>	<b>48.95±0.24</b>	<b>49.01±0.28</b>	21.03±0.32	<b>57.77±0.19</b>	<b>65.23±0.23</b>	<b>65.01±0.26</b>	<b>64.77±0.28</b>	<b>36.09±0.29</b>
Swin-L	–	49.87±0.15	65.23±0.18	52.03±0.23	51.42±0.25	30.81±0.29	69.50±0.17	85.29±0.20	<b>72.23±0.23</b>	72.62±0.25	46.02±0.27
	✓	<b>51.18±0.15</b>	<b>66.79±0.14</b>	<b>53.02±0.21</b>	<b>52.28±0.22</b>	<b>32.87±0.27</b>	<b>70.28±0.15</b>	<b>85.98±0.17</b>	72.15±0.22	<b>73.48±0.24</b>	<b>47.39±0.26</b>