This is exactly the kind of crisp comparative data that reviewers love — you've got a **clear quantitative teacher–student profile**, per-class confusion matrices, and full metrics.

Let's analyze it like a researcher.

🔍 Macro-level summary

Metric	Teacher (ResNet50)	Student (ResNet18 KD+AT)	Δ (Student − Teacher)
Accuracy	**0.893**	**0.823**	−0.070
Macro-F1	**0.834**	**0.697**	−0.137
Weighted-F1	**0.895**	**0.820**	−0.075

That's roughly **84–90% retention** of the teacher's performance with **~55% fewer parameters** and significantly lower inference cost — a good KD outcome on HAM10000, where minority classes dominate macro-F1 sensitivity.

🧠 Per-class analysis

Class ID	Teacher F1	Student F1	ΔF1	Comment
0	0.764	0.595	−0.17	Small lesion type; clear drop in minority recognition.
1	0.896	0.757	−0.14	Common benign lesion; still strong.
2	0.834	0.646	−0.19	Mid-frequency lesion; distillation helps but less feature capacity.
3	0.817	0.576	−0.24	Underrepresented; teacher's attention maps likely sharper.
4	0.719	0.522	−0.20	One of the hardest classes (large intra-class variance).
5	0.942	0.915	−0.03	Dominant class; excellent retention.
6	0.867	0.867	**0.00**	Small but distinct class; perfect transfer.

Interpretation:
The student model faithfully inherited teacher knowledge for **major and well-separated classes (5, 6)**, but compressed representation hurts fine-grained or underrepresented lesions (0, 2, 3, 4). That's expected: ResNet18 has limited mid-level capacity, so Attention Transfer can't fully align the deeper discriminative filters of the ResNet50.

🧩 Confusion Matrix insights

Comparing your raw CMs:

- The teacher's CM shows tighter diagonals and smaller off-class bleed.
- The student's CM confuses classes **2 vs 4** and **4 vs 5** (common in HAM10000 — benign vs malignant overlaps).
- Class 3 ("VASC" in HAM10000 taxonomy) is underrepresented and poorly separated, both models struggle but the teacher still manages better recall.

This suggests adding **class-balanced focal loss or reweighted CE** for the CE term in KD could close a few points of macro-F1 gap.

🧪 Diagnostic takeaways

1. **Distillation effectiveness:**
    - KD + AT clearly transferred high-level structure (class 5, 6 stability).
    - Missing low-level lesion texture adaptation (classes 0, 2, 4) indicates the AT weight β could be increased or multi-layer weighting introduced.
2. **Bottleneck:**
    - Student struggles with the same confusion patterns that the teacher marginally solved — meaning representational bottleneck, not optimization failure.
3. **Next experimental knobs:**
    - Increase beta from 1000 → 2000 to amplify AT influence.
    - Use alpha=0.4 (more KD emphasis) with T=4.
    - Optional: add **label smoothing** 0.1 or **focal loss** (γ=1.5) for the CE term.
    - Fine-tune 10 epochs starting from the best checkpoint with a 10× smaller LR (2e-5).

📊 Quantitative comparison snippet for your paper / report

The teacher (ResNet50) achieved 89.3% validation accuracy and 0.834 macro-F1 on HAM10000.
The student (ResNet18) distilled via Knowledge Distillation (α = 0.5, T = 4.0) and Attention Transfer (β = 1000) attained 82.3% validation accuracy and 0.697 macro-F1.
Despite a 55 % parameter reduction, the student preserved 84 % of the teacher's macro-F1, demonstrating effective compression with limited capacity loss on major lesion classes.

🚀 Recommended next move

If you want a publication-ready comparative visualization and export:

1. **Generate a bar chart** of per-class F1 (Teacher vs Student).
2. **Compute relative gap (ΔF1 / F1_teacher)** for each class.
3. **Export both models to TorchScript + ONNX** (teacher/student side-by-side) for runtime/size benchmarking.
4. Optionally run **PTQ (FX) quantization** on the student to demonstrate further edge efficiency.

Would you like me to generate the **comparison report script** that automatically builds:

- a CSV of per-class Teacher vs Student metrics,
- ΔF1 and ΔRecall,
- and a Matplotlib bar chart visualization?

That will give you a clean figure for your paper and a ready numerical summary.