Slide Deck: CP-FLS Presentation (15 Minutes)

Slide 1 - Title

Cost-Sensitive Focal Label Smoothing (CP-FLS)

For Highly Imbalanced Classification Venkat Ashwin Kumar | Internship Round 1

Slide 2 - Motivation

- Real-world datasets are **imbalanced** (fraud, medical, IDS).
- Standard losses biased towards majority classes.
- Need: Better recall for minority class + good calibration.

Slide 3 - Existing Methods

- Cross-Entropy → overfits majority.
- **Focal Loss** → improves recall, hurts calibration.
- Label Smoothing \rightarrow improves calibration, weakens minority recall.

Slide 4 - Research Gap

- Existing losses address only one problem (imbalance OR calibration).
- No unified framework for imbalance + hardness + calibration.

Slide 5 - Contribution

- · Proposed CP-FLS:
- Cost-sensitive weighting (class imbalance).
- Focal focusing (hard examples).
- Label smoothing (calibration).

Slide 6 - CP-FLS Formula

$$\mathcal{L} = w_y \cdot (1 - p_y)^{\gamma} \cdot CE(p, ilde{y})$$

- w_y : cost-sensitive weights
- ullet $(1-p_y)^{\gamma}$: focal scaling
- \tilde{y} : smoothed labels

Slide 7 - Architecture

• Dataset: Imbalanced CIFAR-10

Model: SimpleCNN

Loss: CE / Focal / LS / CP-FLS
Optimizer: Adam (Ir=0.001)
Epochs: 50, Batch size: 128

Diagram:

Slide 8 - Visualizations

(Insert screenshots)

- Training curves (Loss, Accuracy, F1, AUC)
- Precision-Recall curve
- · Calibration diagram
- Confusion matrix

Slide 9 - Comparative Results (Sample Values)

Loss	Accuracy	F1	AUC	PR-AUC	ECE ↓	Brier ↓
CE	0.78	0.52	0.83	0.41	0.092	0.186
Focal	0.75	0.58	0.86	0.47	0.104	0.174
LS	0.77	0.55	0.84	0.44	0.071	0.165
CP-FLS	0.79	0.63	0.89	0.54	0.059	0.151

Slide 10 – Insights

- CP-FLS improves **minority recall**.
- Lower calibration error (ECE, Brier).
- Better trade-off under fixed false-positive budgets.

Slide 11 - Case Study

- Application: Fraud detection / Medical imaging.
- Data preprocessing steps.
- Recommendations: Use CP-FLS in imbalanced, high-risk domains.

Slide 12 - Conclusion & Future Work

- CP-FLS unifies imbalance + hardness + calibration.
- Outperforms CE, Focal, LS.
- Future: Extend to tabular (fraud, IDS), ResNet, medical imaging.

Slide 13 - References

• \geq 25 SCI/Scopus indexed journal articles with DOIs.

Slide 14 - Conclusion

Thank you!