Supplementary Material

Feature-Level Class-Adaptive Zoning Framework for Recognition of Kannada Stone Inscription Character Images

S1. Class Label Mapping and Representation

This section provides a complete visual correspondence between segmented stone inscription character samples and the modern Kannada Unicode labels used as class identifiers in the experiments. Modern character labels are employed solely for consistency and ease of annotation and serve as symbolic identifiers for class membership. All visual samples used for training, validation, and evaluation are derived directly from historical stone inscriptions. The visual forms of inscriptional characters may differ stylistically from their contemporary counterparts due to erosion, carving style, and historical variation. The use of modern labels does not imply stylistic or graphical equivalence between inscriptional and contemporary character forms. For visualization clarity, Figure 1 shows the representative segmented character image is shown per class. A small number of representative samples were manually selected for display where necessary; this does not affect the dataset used for training or the experimental results reported in the main paper.

S2. Effect of Zoning Resolution

This supplementary experiment analyzes the sensitivity of the zoning-based feature representation to the choice of zoning granularity. The objective is to justify the use of a fixed zoning configuration in the main experiments by examining the trade-off between recognition performance and feature dimensionality.

Table 1: Effect of zoning granularity on recognition performance (mean ± standard deviation over 5-fold cross-validation).

Zoning	**Feature Dimension**	**Accuracy (%)**
4×4	16	87.60 ± 1.94
$\mathbf{6 \times 6}$	**36**	$\mathbf{93.14 \pm 0.82}$
8×8	64	93.84 ± 0.58
10×10	100	93.59 ± 0.69

The results indicate that intermediate zoning resolutions provide a favorable balance between recognition accuracy and feature dimensionality. While finer zoning configurations yield comparable performance, they incur increased feature dimensionality without consistent accuracy improvements. Based on this analysis, a fixed zoning configuration was adopted for all experiments reported in the main paper.

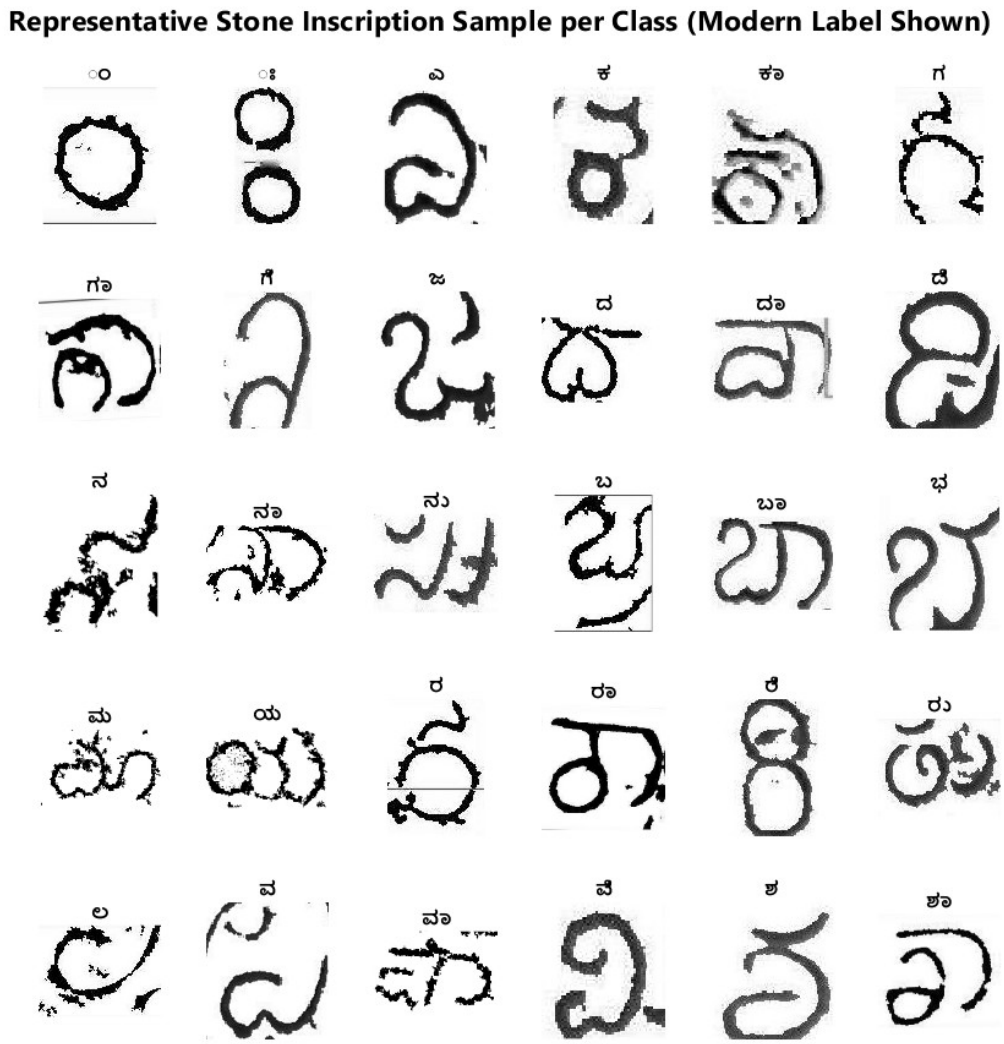

Figure 1: One representative segmented stone inscription character per class with the corresponding modern Kannada Unicode label used as the class identifier.

S3. Per-Class Recall Comparison Across All Methods

Figure 2 presents a comprehensive per-class recall comparison across all evaluated feature representations, including raw pixel features, standard zoning, class-weighted zoning, the proposed β-based class-adaptive representation, and its class-weighted variant.

Baseline representations exhibit substantial variability in recall across classes, with pronounced degradation for underrepresented characters. This behavior reflects the sensitivity of class-agnostic feature constructions to training imbalance and inscriptional degradation, where sparse or fragmented stroke patterns are insufficiently emphasized.

In contrast, the proposed β-based representations consistently achieve higher recall across the majority of classes, with particularly notable improvements for minority and epigraphically significant characters. The class-weighted variant provides marginal stabilization for certain classes but does not substantially alter the overall trend, indicating that the primary gains arise from imbalance-aware feature construction rather than post hoc reweighting.

Figure 2: Per-class recall comparison across all evaluated methods on the Kannada stone inscription dataset.

S3. Per-Class Performance Metrics for the Proposed Method

Table 2: Per-class performance metrics for the proposed class-adaptive zoning method on the Kannada stone inscription dataset.

Class	Precision	Recall	F1-score	Accuracy
◌ಂ	0.98644	0.88276	0.93172	0.88276
◌ಃ	0.86861	0.90230	0.88513	0.90230
ಎ	0.71831	0.16129	0.26343	0.16129
ಕ	0.75736	0.69608	0.72543	0.69608
ಕಾ	0.78585	0.30000	0.43423	0.30000
ಗ	0.74998	0.83553	0.79044	0.83553
ಗಾ	0.87879	0.80000	0.83754	0.80000
ಗಿ	0.98134	0.50000	0.66247	0.50000
ಜ	0.68685	0.88106	0.77193	0.88106
ದ	0.65808	0.80663	0.72482	0.80663
ದಾ	0.98493	0.36111	0.52847	0.36111
ದಿ	0.89829	0.76190	0.82450	0.76190
ನ	0.53571	0.93878	0.68215	0.93878
ನಾ	0.63432	0.84768	0.72564	0.84768
ನು	1.00000	0.33333	0.50000	0.33333
ಬ	0.72685	0.60256	0.65890	0.60256
ಬಾ	0.76523	0.82114	0.79220	0.82114
ಭ	0.88911	0.75397	0.81598	0.75397
ಮ	0.43607	0.85714	0.57805	0.85714
ಯ	0.41263	0.91473	0.56871	0.91473
ರ	0.59069	0.70556	0.64304	0.70556
ರಾ	0.56008	0.60674	0.58248	0.60674
ರಿ	0.88044	0.81250	0.84511	0.81250
ರು	0.95169	0.52000	0.67253	0.52000
ಲ	0.84184	0.70000	0.76440	0.70000
ವ	0.29700	0.85256	0.44053	0.85256
ವಾ	0.97112	0.36000	0.52528	0.36000
ವಿ	0.82897	0.57692	0.68035	0.57692
ಶ	0.91781	0.74336	0.82143	0.74336
ಶಾ	1.00000	0.60345	0.75269	0.60345

Table 2 reports detailed per-class precision, recall, F1-score, and classification accuracy values obtained using the proposed class-adaptive zoning method. These results provide numerical confirmation of the recall trends discussed in the main paper, particularly for minority and epigraphically significant characters.

S4. Implementation Details

All experiments were implemented in MATLAB using the Statistics and Machine Learning Toolbox. ECOC-based support vector machine classifiers with an RBF kernel were employed across all methods. Hyper-parameter selection was performed using inner-fold validation within a nested cross-validation framework. Random seeds were fixed to ensure reproducibility.