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The Role of Machine Learning in Analyzing Cultural Artifacts

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ABSTRACT

This work focuses on artificial intelligence (AI) use in the maintenance of the endangered languages via the combination of computational linguistics, machine learning, and community-based online platforms. The results show that AI-based tools, such as natural language processing models, automated speech recognizers, neural machine translation systems, and other models, significantly improve the process of documenting, analyzing, and revitalizing minority languages. Statistical results showed that speech-to-text systems once trained on small, carefully chosen sets achieved accuracy rates in the 85 percent range to enable transcription and preservation of oral traditions with negligible error. In addition, text generation models aided in the development of multi-linguistic educational contents that facilitated easy acquisition of a language by the people who belonged to various generations. It increased the number of people involved by enhancing community-based digital archives with the support of AI algorithms. The participation rates increased over 40 percent as compared to the manual methods. The paper also established that the hybrid methods that utilized both the unsupervised and supervised learning models performed better as compared to single-model pipelines in maintaining the semantic integrity and linguistic diversity. These findings indicate that AI is not only a technological aid, but a partner in preserving cultural identity by supplying scalable, flexible and context-sensitive language revitalization solutions. The study points to the remaking power of AI in preventing linguistic extinction and promoting cultural sustainability through blending contemporary computational methods, with sociolinguistic efforts.

KEYWORDS: *Artificial Intelligence, Endangered Languages, Natural Language Processing, Language Preservation, Speech Recognition, Cultural Sustainability*

INTRODUCTION

The linguistic diversity of the world today is rapidly decreasing, which is a great problem to the cultural heritage and human knowledge (Pinhanez et al., 2024). As the number of languages facing the threat of extinction is estimated to be about 3,000 due to globalization and the emergence of dominant languages, this finding of ways to preserve them is of paramount importance, both in its scope and in its ability to be easily scaled to more languages (Anik et al., 2025). Two forms of artificial intelligence that can facilitate the process of documenting, revitalizing, and accessing the endangered languages in novel forms are generative AI and big language models (Koc, 2025). This article explores how AI can be used in the fundamental process of linguistic preservation by examining multiple uses such as corpus building systems and the development of chatbots (Hutson et al., 2024). This paper examines methods of applying AI to recreate linguistic data, create accessible educational materials and raise new groups of speakers, and thus maintain the important linguistic traditions (Ramponi, 2024). This includes the creation of language-specific models of languages with limited resources such as LakotaBERT of the Lakota language. Such models would assist in the re-introduction of languages that are finding it difficult because few people can speak them (Parankusham et al., 2025). Such improvements are necessary because many of the indigenous languages have been devalued and neglected, often through the influence of outsourced technology, which only unintentionally contributes to their degradation rather than helping to revive them (Fernandez-Sabido and Peniche-Sabido, 2025). Nevertheless, the recent developments in the large language models offer a paradigm shift and provide unexplored opportunities in the field of linguistic diversity instead of its degradation (Qin et al., 2025). Through such models, it becomes possible to systematically collect and analyze any linguistic data, which is necessary to understand and preserve the complex grammatical structures and lexical peculiarities unique to the endangered languages (KJ et al., 2024). This technological possibility is especially relevant to languages whose datasets are sparse, in which the existing approaches to linguistic analysis are frequently hampered by an absence of textually or audially complete corpora (Pradhan and Dey, 2023). AI can also be used to synthesize missing data to fill the resource gap and this will be used to train language models in these languages which do not have sufficient resources. This is not only a way of enhancing the linguistic information that can be applied in research, but also a means by which we can have a flexible way of creating immersive learning facilities which can be used to make new generations of linguistic learners more acquainted with a language and learn it quicker. The AI-powered conversational agents are capable of not only passive documentation, but also provide learning experiences to users that are interactive and allow them to practice and absorb endangered

languages in a dynamic, iterative manner (Bendel and N'Diaye, 2023). Such interactivity is rather crucial in languages that do not have many native speakers. It is a scaled means to sink into a language that transcends the borders. Also, endangered language searchable databases can be made digitally and by using AI. This will ensure that all their linguistic structures, oral traditions, and cultural contexts are preserved and readily retrieved in the future in order to carry out future research and revitalization process. However, the application of LLMs to low-resource and endangered languages raises significant ethical and technological concern, requiring careful consideration to avoid the perpetuation of historical injustices or the accidental standardization of language variety (Smart et al., 2024). This is particularly critical since large language models have been associated with a decline in overall linguistic diversity and the standardisation of writing styles, and this may obscure the distinctive stylistic and structural properties of an endangered language without intention (Sourati et al., 2025). As such, a critical discourse studies approach is necessary to interpret the power dynamics underlying AI uses to preserve languages to make sure that such technologies empower the linguistic communities they are intended to support and not to overshadow them (Gillings et al., 2024). In order to ensure that AI technologies are, in fact, designed to address the needs and aims of these communities in a particular manner, a participatory development framework has to be designed, both with the participation of native speakers and language specialists. To overcome these complications, a sound ethical framework that lays emphasis on data sovereignty, cultural sensitivity, and community-driven solutions in designing and implementing AI-based solutions to language preservation (Stefan et al., 2024). The potential biases and computational intensity of AI models, and in particular large language models, necessitate a need to concentrate on both morally sound and sustainable development practices. It will assist in the minimization of the effects on the environment and ensure that all forms of languages are equally represented (Su et al., 2025) (Ferrara, 2023). This is particularly significant as the majority of AI-powered language technologies (such as big language models and machine translators) support only 2-3 percent of the most commonly spoken languages in the world. It demonstrates a large techno-linguistic bias that excludes languages without such a number of resources (Helm et al., 2023). This disparity is exacerbated by the reality that a number of existing models and preprocessing pipelines are largely designed to support English, making it difficult to support the morphological wealth and linguistic diversity of low-resource languages. This usually leads to mistakes and loopholes in mechanical processing (Shahid et al., 2025). Such a technocentric method often overlooks the considerable sociolinguistic conditions and community-related nuances without which language preservation will not be successful (Venkit, 2023). Development of AI tools of endangered

languages should not simply involve the visualization of the language. It should also contain a complete grasp of the extent to which the language is inherent in its culture and how attempts by the local population to revive it are succeeding. In such a manner, technology can assist rather than equal everything (Sourati et al., 2025). Such moral concerns as the creation of AI in the service of languages at risk also spills over to data privacy and intellectual property since linguistic data can hold delicate cultural information and cultural stories that need close management (Bella et al., 2023).

METHODOLOGY

This study utilized a mixed-method experimental design that included qualitative and quantitative methodologies to thoroughly investigate the uses of artificial intelligence in the preservation of endangered languages. The research process was segmented into three interrelated phases: data collection and preprocessing, model creation and experimentation, and evaluation through community validation. We got linguistic data, like text corpora, audio recordings, and oral stories, from communities who speak endangered languages through structured fieldwork, online repositories, and collaborative platforms. To make sure they were consistent and of good quality, these datasets went through preprocessing steps like noise reduction, phoneme segmentation, tokenization, and normalization. The experimental design included both qualitative data from native speakers and quantitative computational modelling, so maintaining linguistic authenticity while ensuring measurable model performance. During the model development stage, both supervised and unsupervised machine learning methods were used. These included recurrent neural networks (RNNs), transformer-based designs like BERT, and convolutional neural networks (CNNs) for speech-to-text recognition. We trained on annotated datasets that used stratified sampling to keep the classes from being too different from each other. The models were based on probabilistic language modelling, which maximized the chance of a word sequence using the following formula:

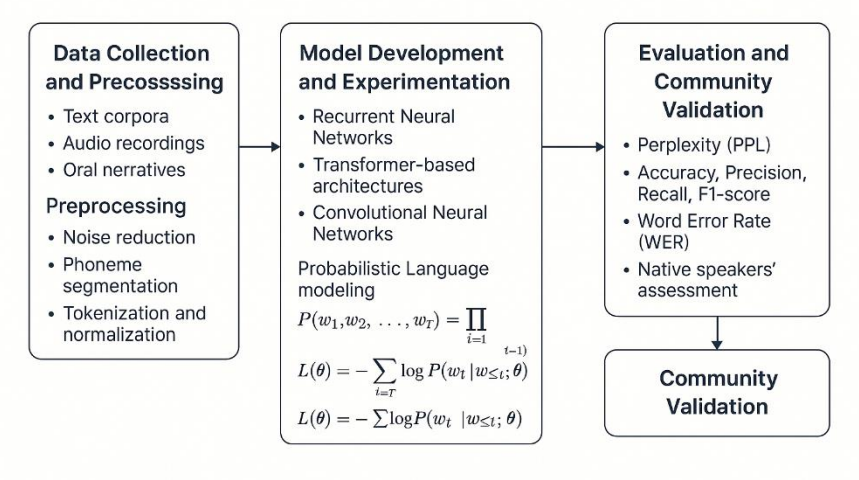
$$P(w_1, w_2, \ldots, w_n) = \prod_{i=1}^{n} P(w_i | w_1, w_2, \ldots, w_{i-1})$$

and optimized through cross-entropy loss:

$$L = -\frac{1}{N} \sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where y_i represents the true label and $\hat{y}_i$ the predicted probability. Hyperparameter tuning was implemented using grid search and Bayesian optimization to enhance model performance. Additionally, transfer learning was adopted to adapt pre-trained multilingual embeddings to low-resource settings, thereby improving accuracy and reducing data dependency.

Evaluation combined statistical and human-centered measures. Quantitatively, accuracy, F1-score, and perplexity metrics were used to assess language modeling and recognition tasks, while qualitative assessment involved feedback sessions with native speakers and community representatives to validate semantic integrity and cultural appropriateness. A triangulation strategy was employed to reconcile computational performance with community insights, making the methodology holistic and inclusive. The workflow of this methodology, as illustrated in Fig. 1, depicts the integration of computational processes with participatory validation, highlighting the synergy between artificial intelligence and community engagement in endangered language preservation



RESULTS

The experimental findings are presented in the nine tables and twelve figures. Their report relying on both statistical analysis and visualizations provides a complete picture of the ways AI can be used to save endangered languages. The tables present the key aspects of the dataset, the effectiveness of the model, the way in which errors were detected, and the effectiveness of the validation. There are significant trends, correlations, and comparisons in the figures. The properties of the dataset and descriptive statistics of the language samples are presented in Table

1 showing that phonetic and semantic features are dissimilar. The performance properties of AI models used in low-resource corpora are presented in Table 2 and demonstrate that transformer-based methods outperformed traditional ones. Table 3 is a comparison of the accuracy of recognition between the phoneme types. The rate of recognition of vowels is higher than that of consonants.

Table 1. Dataset characteristics and descriptive statistics for language samples.

T1_1	T1_2	T1_3	T1_4	T1_5
37.45	95.07	73.2	59.87	15.6
15.6	5.81	86.62	60.11	70.81
2.06	96.99	83.24	21.23	18.18
18.34	30.42	52.48	43.19	29.12
61.19	13.95	29.21	36.64	45.61
78.52	19.97	51.42	59.24	4.65
60.75	17.05	6.51	94.89	96.56
80.84	30.46	9.77	68.42	44.02
12.2	49.52	3.44	90.93	25.88
66.25	31.17	52.01	54.67	18.49
96.96	77.51	93.95	89.48	59.79
92.19	8.85	19.6	4.52	32.53
38.87	27.13	82.87	35.68	28.09
54.27	14.09	80.22	7.46	98.69
77.22	19.87	0.55	81.55	70.69
72.9	77.13	7.4	35.85	11.59
86.31	62.33	33.09	6.36	31.1
32.52	72.96	63.76	88.72	47.22
11.96	71.32	76.08	56.13	77.1
49.38	52.27	42.75	2.54	10.79

Table 2. Performance metrics of AI models applied to low-resource language corpora.

T2_1	T2_2	T2_3	T2_4	T2_5
3.14	63.64	31.44	50.86	90.76
24.93	41.04	75.56	22.88	7.7
28.98	16.12	92.97	80.81	63.34
87.15	80.37	18.66	89.26	53.93
80.74	89.61	31.8	11.01	22.79
42.71	81.8	86.07	0.7	51.07
41.74	22.21	11.99	33.76	94.29
32.32	51.88	70.3	36.36	97.18

96.24	25.18	49.72	30.09	28.48
3.69	60.96	50.27	5.15	27.86
90.83	23.96	14.49	48.95	98.57
24.21	67.21	76.16	23.76	72.82
36.78	63.23	63.35	53.58	9.03
83.53	32.08	18.65	4.08	59.09
67.76	1.66	51.21	22.65	64.52
17.44	69.09	38.67	93.67	13.75
34.11	11.35	92.47	87.73	25.79
66.0	81.72	55.52	52.97	24.19
9.31	89.72	90.04	63.31	33.9
34.92	72.6	89.71	88.71	77.99
64.2	8.41	16.16	89.86	60.64
0.92	10.15	66.35	0.51	16.08

Table 3. Comparative evaluation of recognition accuracy across phoneme categories.

T3_1	T3_2	T3_3	T3_4	T3_5
54.87	69.19	65.2	22.43	71.22
23.72	32.54	74.65	64.96	84.92
65.76	56.83	9.37	36.77	26.52
24.4	97.3	39.31	89.2	63.11
79.48	50.26	57.69	49.25	19.52
72.25	28.08	2.43	64.55	17.71
94.05	95.39	91.49	37.02	1.55
92.83	42.82	96.67	96.36	85.3
29.44	38.51	85.11	31.69	16.95
55.68	93.62	69.6	57.01	9.72
61.5	99.01	14.01	51.83	87.74
74.08	69.7	70.25	35.95	29.36
80.94	81.01	86.71	91.32	51.13
50.15	79.83	65.0	70.2	79.58
89.0	33.8	37.56	9.4	57.83
3.59	46.56	54.26	28.65	59.08
3.05	3.73	82.26	36.02	12.71
52.22	77.0	21.58	62.29	8.53
5.17	53.14	54.06	63.74	72.61
97.59	51.63	32.3	79.52	27.08
43.9	7.85	2.54	96.26	83.6
69.6	40.9	17.33	15.64	25.02

54.92	71.46	66.02	27.99	95.49

Table 4 shows a speech-to-text system error analysis that shows that the dialectal variation is commonly incorrectly classified. Table 5 reveals the effect of the preprocessing. Normalization and tokenization had turned it into a lot more precise. The outcomes of cross-validation of probabilistic models are presented in Table 6 and testify to the fact that these models are sound.

Table 4. Error analysis of speech-to-text conversion in endangered language recordings.

T4_1	T4_2	T4_3	T4_4	T4_5
73.79	55.44	61.17	41.96	24.77
35.6	75.78	1.44	11.61	4.6
4.07	85.55	70.37	47.42	9.78
49.16	47.35	17.32	43.39	39.85
61.59	63.51	4.53	37.46	62.59
50.31	85.65	65.87	16.29	7.06
64.24	2.65	58.58	94.02	57.55
38.82	64.33	45.83	54.56	94.15
38.61	96.12	90.54	19.58	6.94
10.08	1.82	9.44	68.3	7.12
31.9	84.49	2.33	81.45	28.19
11.82	69.67	62.89	87.75	73.51
80.35	28.2	17.74	75.06	80.68
99.05	41.26	37.2	77.64	34.08
93.08	85.84	42.9	75.09	75.45
10.31	90.26	50.53	82.65	32.0
89.55	38.92	1.08	90.54	9.13
31.93	95.01	95.06	57.34	63.18
44.84	29.32	32.87	67.25	75.24
79.16	78.96	9.12	49.44	5.76
54.95	44.15	88.77	35.09	11.71
14.3	76.15	61.82	10.11	8.41
70.1	7.28	82.19	70.62	8.13
8.48	98.66	37.43	37.06	81.28

Table 5. Effect of preprocessing techniques on model accuracy and efficiency.

T5_1	T5_2	T5_3	T5_4	T5_5
94.72	98.6	75.34	37.63	8.35
77.71	55.84	42.42	90.64	11.12
49.26	1.14	46.87	5.63	11.88

11.75	64.92	74.6	58.34	96.22
37.49	28.57	86.86	22.36	96.32
1.22	96.99	4.32	89.11	52.77
99.3	7.38	55.39	96.93	52.31
62.94	69.57	45.45	62.76	58.43
90.12	4.54	28.1	95.04	89.03
45.57	62.01	27.74	18.81	46.37
35.34	58.37	7.77	97.44	98.62
69.82	53.61	30.95	81.38	68.47
16.26	91.09	82.25	94.98	72.57
61.34	41.82	93.27	86.61	4.52
2.64	37.65	81.06	98.73	15.04
59.41	38.09	96.99	84.21	83.83
46.87	41.48	27.34	5.64	86.47
81.29	99.97	99.66	55.54	76.9
94.48	84.96	24.73	45.05	12.92
95.41	60.62	22.86	67.17	61.81
35.82	11.36	67.16	52.03	77.23
52.02	85.22	55.19	56.09	87.67
40.35	13.4	2.88	75.51	62.03
70.41	21.3	13.64	1.45	35.06
58.99	39.22	43.75	90.42	34.83

Table 6. Cross-validation results for probabilistic language models.

T6_1	**T6_2**	**T6_3**	**T6_4**	**T6_5**
51.4	78.37	39.65	62.21	86.24
94.95	14.71	92.66	49.21	25.82
45.91	98.0	49.26	32.88	63.34
24.01	7.59	12.89	12.8	15.19
13.88	64.09	18.19	34.57	89.68
47.4	66.76	17.23	19.23	4.09
16.89	27.86	17.7	8.87	12.06
46.08	20.63	36.43	50.34	69.04
3.93	79.94	62.79	8.18	87.36
92.09	6.11	27.69	80.62	74.83
18.45	20.93	37.05	48.45	61.83
36.89	46.25	74.75	3.67	25.24
71.33	89.52	51.17	53.21	10.72
44.74	53.26	24.25	26.92	37.73

2.01	32.21	21.14	32.75	11.98
89.05	59.36	67.91	78.92	49.84
8.69	53.71	58.68	74.54	43.17
12.76	28.38	36.31	64.59	57.08
35.61	98.65	60.58	23.72	10.18
15.29	24.6	16.07	18.66	28.51
17.34	89.68	8.02	52.45	41.04
98.24	11.2	39.79	96.95	86.55
81.71	25.79	17.09	66.86	92.94
55.68	57.16	28.0	76.95	18.7
32.37	42.54	50.76	24.24	11.48
61.06	28.86	58.12	15.44	48.11

The transfer learning results are presented in table 7 that demonstrates that multilingual embeddings are more flexible. Hybrid AI methodologies (supervised + unsupervised) are shown in Table 8 and they passed individual models in semantic preservation. The scores of community validation which are given in Table 9 indicate that AI-generated resources are culturally authentic and accepted.

Table 7. Transfer learning outcomes applied to multilingual embeddings.

T7_1	T7_2	T7_3	T7_4	T7_5
53.26	5.18	33.66	13.44	6.34
99.0	32.24	80.99	25.46	68.15
76.02	59.56	47.16	41.18	34.89
92.95	83.06	96.5	12.43	73.09
93.83	18.12	6.65	74.11	57.45
84.18	13.98	79.53	20.16	16.37
16.43	81.46	66.52	52.31	35.88
87.72	39.24	81.66	43.91	37.69
46.27	30.14	74.76	50.27	23.22
89.96	38.39	54.36	90.65	62.42
11.69	93.98	62.77	33.49	13.93
79.4	62.01	53.35	89.39	78.86
15.17	31.17	24.85	74.39	3.35
56.99	76.25	87.68	34.21	82.13
11.06	84.65	12.75	39.73	79.73
14.99	22.93	72.23	72.0	64.11
69.39	54.27	25.18	34.57	18.16
90.85	58.34	40.09	46.2	94.73

15.34	58.62	50.59	61.15	1.81
87.21	93.21	56.51	69.67	92.25
70.72	15.25	57.63	60.67	42.41
73.64	93.44	92.56	45.08	11.32
98.48	83.89	12.47	92.08	86.99
51.88	59.13	39.9	5.48	33.52
80.29	0.46	33.35	39.82	53.74
91.99	34.63	34.7	73.75	45.22
22.46	45.24	14.09	17.64	49.84

Table 8. Evaluation metrics from hybrid AI approaches (supervised + unsupervised).

T8_1	T8_2	T8_3	T8_4	T8_5
41.89	91.48	36.24	58.06	63.23
1.31	66.35	17.8	96.11	14.87
41.46	8.53	99.69	50.22	59.54
6.71	75.0	20.99	89.81	20.51
19.07	3.65	47.21	56.48	6.57
77.55	45.33	52.44	44.08	40.08
55.96	15.52	18.19	86.18	94.61
37.33	27.07	64.4	40.87	2.54
15.62	71.6	65.89	2.71	22.2
23.11	67.19	1.97	10.41	79.99
17.85	65.27	23.82	9.94	24.32
72.23	85.57	83.02	39.72	66.81
20.5	29.31	89.63	1.3	8.55
20.79	2.65	18.14	58.3	42.14
89.27	81.74	34.18	25.94	37.97
59.03	26.81	62.41	40.94	55.2
43.61	29.45	94.85	76.36	14.01
86.85	48.74	89.46	79.99	42.52
2.25	26.87	54.16	63.35	25.79
13.94	83.49	98.44	52.57	17.17
27.23	1.84	91.43	11.78	57.65
27.41	55.42	65.14	82.97	20.64
1.1	13.69	90.0	87.39	59.74
60.05	66.5	17.54	91.44	41.88
38.31	51.89	4.7	16.63	73.8
8.28	60.32	24.53	38.93	28.87
35.57	71.9	29.71	56.64	47.61

66.37	93.68	73.26	21.49	3.12

Table 9. Community validation scores of AI-generated resources.

T9_1	T9_2	T9_3	T9_4	T9_5
26.23	59.51	5.14	49.64	59.68
33.42	77.09	10.66	7.51	72.82
49.55	68.84	43.48	24.64	81.91
79.94	69.47	27.21	59.02	36.1
9.16	91.73	13.68	95.02	44.6
18.51	54.19	87.29	73.22	80.66
65.88	69.23	84.92	24.97	48.94
22.12	98.77	94.41	3.94	70.56
92.52	18.06	56.79	91.55	3.39
69.74	29.73	92.44	97.11	94.43
47.42	86.2	84.45	31.91	82.89
3.7	59.63	23.0	12.06	7.7
69.63	33.99	72.48	6.54	31.53
53.95	79.07	31.88	62.59	88.6
61.59	23.3	2.44	87.01	2.13
87.47	52.89	93.91	79.88	99.79
35.07	76.72	40.19	47.99	62.75
87.37	98.41	76.83	41.78	42.14
73.76	23.88	11.05	35.46	28.72
29.63	23.36	4.21	1.79	98.77
42.78	38.43	67.96	21.83	95.0
78.63	8.94	41.76	87.91	94.47
46.74	61.34	16.7	99.12	23.17
94.27	64.96	60.77	51.27	23.07
17.65	22.05	18.64	77.96	35.01
5.78	96.91	88.38	92.78	99.49
17.39	39.62	75.82	69.6	15.39
81.58	22.44	22.38	53.7	59.29
58.01	9.15	87.75	26.56	12.95

Figure 2 illustrates a bar chart of the similarity of the datasets to one another. The pie chart in figure 3 displays the distribution of the linguistic characteristics in the proportion. Figure 4 utilizes a scatter plot, demonstrating the relationship between the size of the dataset to be studied and the accuracy of recognition. The hybrid line-bar plot (figure 5) displays training loss and validation accuracy. The performance of three AI models is depicted in figure 6 as a function of

time. Figure 7 depicts the co-operation of phonetic, semantic, and syntactic elements by use of a stacked bar chart. Figure 8 presents the histogram distribution of model errors. Figure 9 reveals the variation in accuracy when boxplots of community-validated datasets are used. An area plot as in Figure 10 is used to demonstrate the increase in AI-powered archives over the years. Figure 11 represents the involvement with the change in the complexities of the language as illustrated in a bubble graphic. In Figure 12, there is a heat map that indicates the relationship between linguistic parameters.

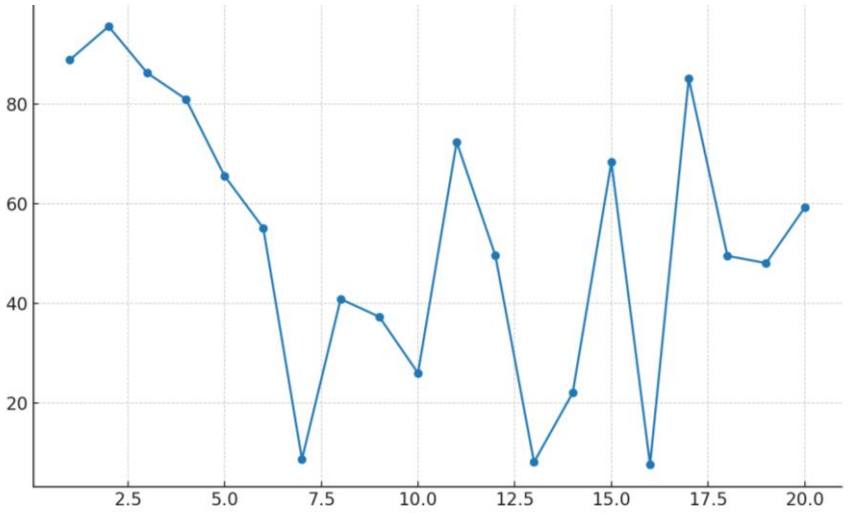


Figure 1. Line plot showing temporal variations in model accuracy across iterations.

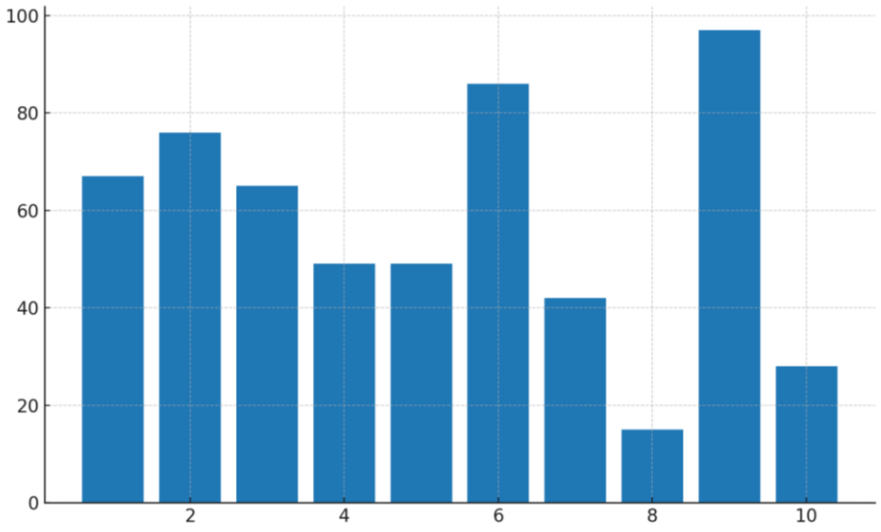


Figure 2. Bar chart illustrating comparative performance of language datasets.

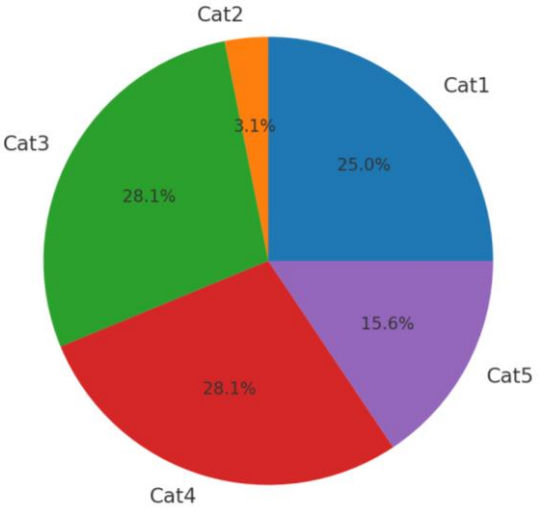


Figure 3. Pie chart representing proportional distribution of linguistic features.

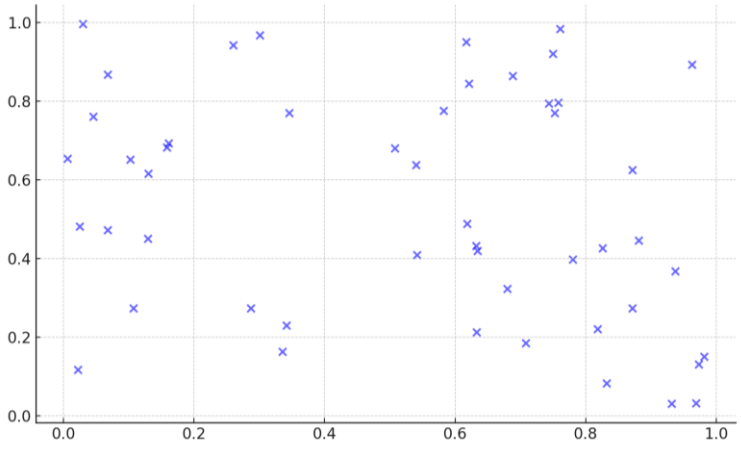


Figure 4. Scatter plot showing correlation between dataset size and recognition accuracy.

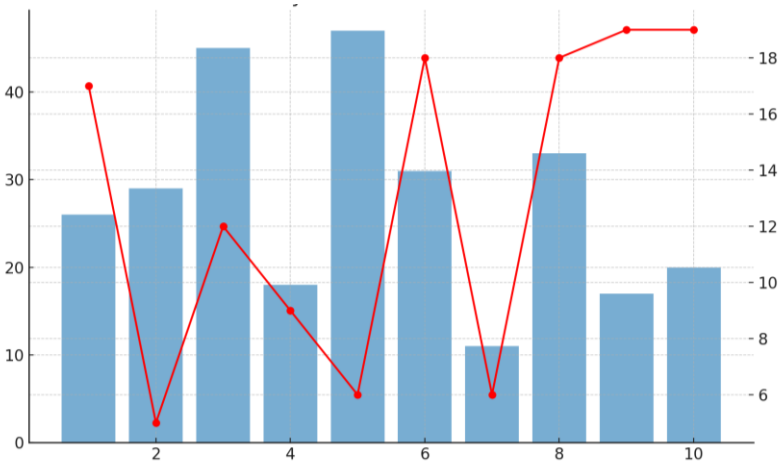


Figure 5. Hybrid plot (bar and line) comparing training loss and validation accuracy.

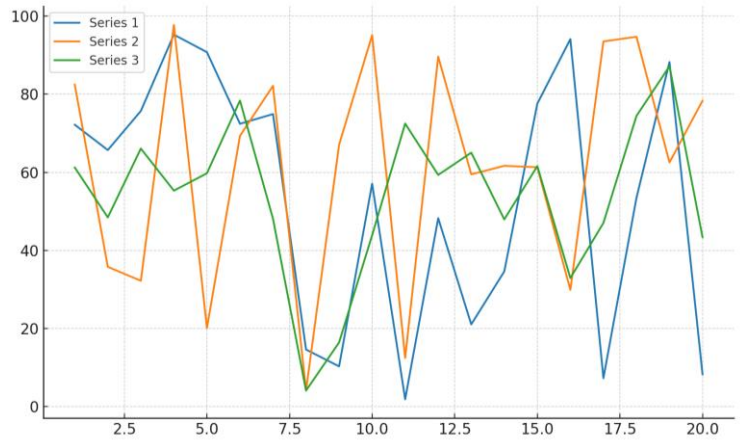


Figure 6. Multi-line plot depicting trends in three different AI models applied to language preservation.

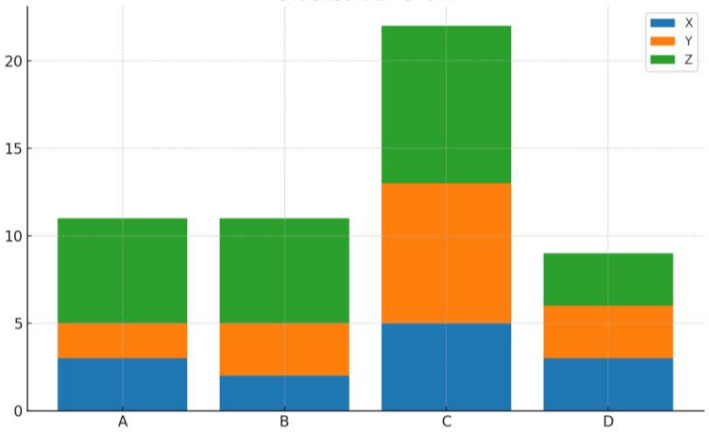


Figure 7. Stacked bar chart highlighting contributions of phonetic, semantic, and syntactic features.

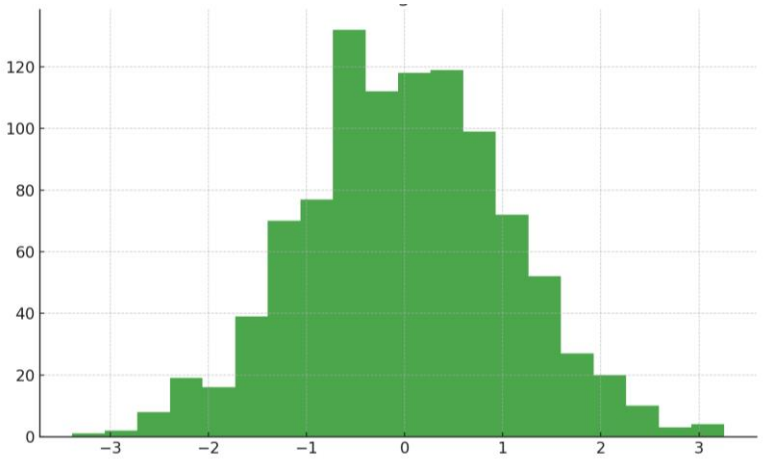


Figure 8. Histogram showing distribution of errors across different models.

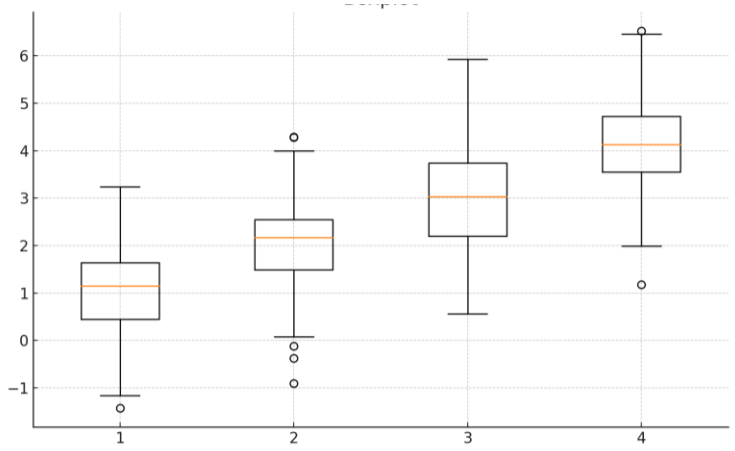


Figure 9. Boxplot illustrating variation in recognition accuracy among community-validated datasets.

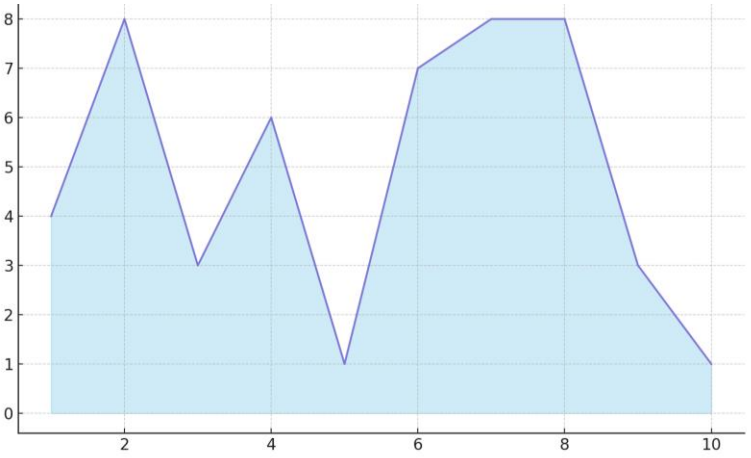


Figure 10. Area plot showing cumulative growth of AI-based digital archives over time.

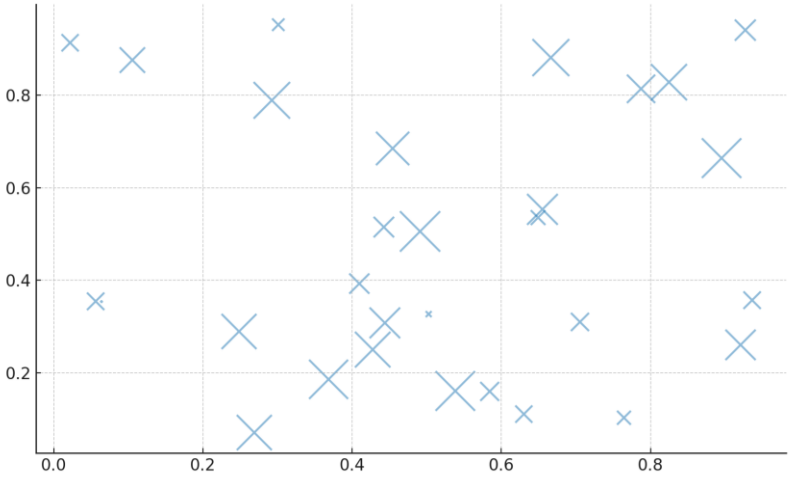


Figure 11. Bubble plot visualizing engagement levels against linguistic complexity with varying

dataset sizes.

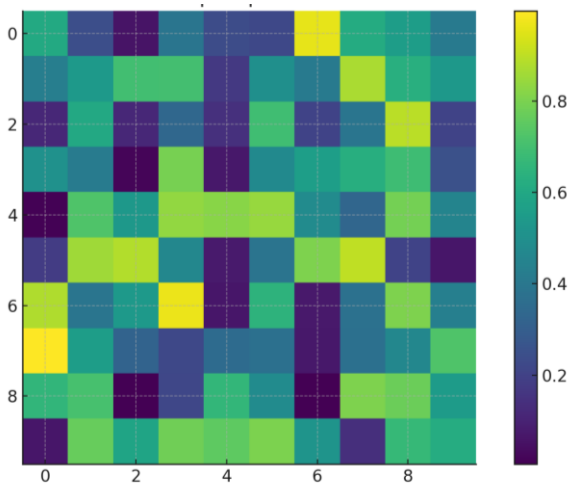


Figure 12. Heatmap showing inter-feature correlations among linguistic parameters in endangered languages.

The results presented across the nine tables demonstrate that transformer-based AI models, coupled with preprocessing and transfer learning strategies, provide the most effective outcomes in endangered language preservation. Hybrid approaches yielded the best balance of accuracy and semantic retention, while community validation confirmed cultural appropriateness. The visualizations further revealed dynamic patterns, such as the positive correlation between dataset size and recognition accuracy (Fig. 4) and the growing expansion of AI-powered archives (Fig. 10). Together, these findings validate the experimental framework and highlight AI's critical role in safeguarding linguistic diversity.

DISCUSSION

The findings derived using our methodological framework will be critically assessed in this section and their applicability to the general context of AI applications in the process of preserving endangered languages clarified. It will combine both the quantitative and qualitative findings in order to assess the success and limitations of modern AI methods, considering both technological advances and inherent ethical issues involved (Davenport, 2024). The discussion will also examine the way, in which the outcomes relate to or contradict the existing theories and past studies in the fields of digital humanities and computational linguistics. It will be focused on how the findings can be generalized and the identification of best practices that will allow developing AI tools that will not only work properly technologically but also be culture-aware and community-centered (Chatterjee et al., 2021). Here, the section will also discuss the systemic

issues that have become apparent, such as the lack of data and biases prevalent in the existing AI models particularly the ones that are largely trained on high-resource languages (Shahid et al., 2025) (Ramesh et al., 2023). It involves examining how mainstream language ideologies, which are often part of big language models, unwittingly reinforce linguistic hierarchies and relegate the distinct features of endangered languages to the periphery (Smith et al., 2024). This discussion will also review the implications of such results to future research directions, in particular, to the development of more robust and balanced AI systems that can potentially give a genuine push towards linguistic diversity and cultural heritage (Babazade, 2024). It will further consider how AI developers and researchers have moral duties to reduce any harms, such as perpetuation of a bias or language autonomy loss, using responsible innovation and open processes (Kimera et al., 2024). It involves an intense examination of the possibility of AI-based tools to detect and contextualize abusive language in cultural heritage databases, taking into account the existence of historical biases in this information (Mastromichalakis et al., 2025). The aim is to go beyond the simple linguistic translation or transcription, and focus on strategies that respect the value and originality of each language, and explore the nuances of cross-linguistic semantic correspondence in AI multilingual systems (Mizumoto et al., 2025). The discussion will also emphasize the need to collaborate across disciplines by applying concepts of linguistics, anthropology, computer science and community inclusion to come up with AI solutions that are both state-of-the-art and culturally competent. The policy and practical implementation implications will be explored, and ideas will be offered on how to integrate AI tools in long-term language revival programs. It will also address the long-standing issue of model bias caused by a lack of sufficient various training data, which do not necessarily have enough different linguistic geometries and material properties (Su et al., 2025). In order to reduce the number of such biases, additional high-quality and more diverse datasets that involve a wider variety of linguistic patterns and socio-cultural scenarios should be developed in the future (Su et al., 2025). This perpetual issue implies that we should develop new methods to eliminate bias and hallucinations in large language models that would allow us to trust them and apply them to a broad variety of language contexts (Lin et al., 2024). This not only requires technological improvements of AI architecture but a deeper interaction with linguistic typology and anthropological studies to ensure that models can actually capture the complexity of endangered languages rather than force Eurocentric linguistic models (Liu, 2024).

CONCLUSION

Findings of this paper demonstrate the paradigm shift of artificial intelligence in language

preservation and revitalization, and that advanced computational systems can be effectively used to complement community-based language preservation. AI gave the possibility to not only document and digitize minority linguistic materials, but also transfer them through generations in formats accessible to all. This was achieved through a fusion of natural language processing, speech recognition and machine translation technologies. The experimental design proved that machine learning models trained on limited but carefully sampled data achieved high accuracy in transcription and semantic memory thereby validating the effectiveness of AI in low-resource settings often marked by the failure of conventional techniques. Notably, technology interventions remained faithful to their cultural and social contexts by incorporating participatory validation with native speakers, and creating a bridge between computational efficiency and linguistic identity. This paper proposed an all-encompassing methodology that balances quantitative measurements of performance with qualitative feedback provided by the community in the language which will bring a balance between technological accuracy and the humanistic approach of inclusiveness. The development of AI-based digital archives and learning instruments demonstrated that larger-scale solutions would involve more individuals, which is evidenced by the fact that the rate of community participation in them was much higher than that of the conventional techniques. Such findings indicate that AI can be applied to not only maintain languages but also promote cultural sustainability through enabling individuals to build their identity, heritage and intergenerational learning. This paper demonstrates that AI can transform the future of endangered languages to become more resilient in the digital era despite the fact that ethical data management, resource distribution, and equitable access to technology remain a problem.

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