EnglishTense: A large-scale English texts dataset categorized into three categories: (Past, Present, Future).

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Abstract

The creation and assessment of a Vanilla Recurrent are presented in this study. Three-tense classification of English sentences using a neural network (RNN) model categories: Future, Present, and Past. Tense categorisation is an essential but difficult task in NLP (natural language processing), with applications in text summarisation, machine translation, and temporal information extraction tion. We make use of a bespoke dataset with roughly 26,633 sentences. (13,824 unique after preprocessing), with tense categories manually labelled. The Class imbalance in the sample is moderate (Future: 36.5 Extensive preprocess- Lowercasing and typo correction (e.g., "aienhanced") were used. "ai enhanced"), text normalisation, and duplicate elimination. A simple RNN architecture tecture was used with a single-layer SimpleRNN (128) embedding layer. units), L2 regularisation, and dropout (0.5) to reduce overfitting.The Adam optimiser and sparse categorical cross-entropy loss with early halting were used to train the model. The results demonstrate outstanding performance, with a macro F1-score of 0.967 and a test accuracy of 96.8. The confusion matrix shows few mistakes, mostly in "will have been" formulations between the Present Perfect Progressive and Future tenses. On this test, the basic vanilla RNN performs better than expected, proving that complicated designs are not necessarily required for great performance. The model's possible vulnerability to extremely lengthy sequences and dataset-specific biases are among its limitations. If the model is used without supervision, it could unethically continue labelling inconsistencies. Future research could compare and expand to aspect and modality categorisation using LSTM/GRU variations, attention processes, or transformer-based models (like BERT).The study maintains computational efficiency while validating the efficacy of classical sequential models in contemporary NLP workloads.

Keywords: tense classification, vanilla RNN, natural language processing, sentence-level tense detection, recurrent neural networks, English tense prediction, NLP dataset preprocessing, overfitting mitigation, temporal tagging, deep learning baseline

1 Introduction

Natural Language Processing (NLP) has made significant progress, yet accurately determining the tense of an English sentence—whether it expresses Past, Present, or Future—remains a challenging and practically important task. Although tense classification appears straightforward, English contains a rich tense–aspect system involving twelve classical tenses, modal constructions, and temporal expressions that do not always rely on verb morphology. Complex structures such as perfect-progressive forms (e.g., "will have been doing"), future-in-the-past constructions (e.g., "was going to"), and sentences where temporal adverbs dominate meaning (e.g., "Tomorrow we meet the president" vs. "Yesterday we met the president") consistently cause misclassification by current commercial NLP tools and even large language models. These errors reduce the performance of downstream applications such as machine translation, temporal information extraction, conversational coherence modelling, automated essay scoring, and language-learning systems.

Transformer-based models (BERT, RoBERTa, T5, etc.) perform well on academic benchmarks, but they introduce substantial drawbacks: extremely high memory and computational needs, slow inference times, limited interpretability, large energy consumption, and vulnerability to overfitting when fine-tuned on small datasets. These limitations make them less suitable for tense classification in real-world, low-resource, or on-device applications. In contrast, lightweight sequential models such as vanilla Recurrent Neural Networks (RNNs) remain efficient, fast, and surprisingly effective for sentence-level tasks where temporal cues are often concentrated in short contexts. However, their potential for tense classification has been underexplored in modern NLP research.

2 Problem Statement

Despite their practical advantages, vanilla RNNs have not been systematically evaluated for the task of English sentence-level tense classification. Moreover, no large, publicly available benchmark dataset exists specifically for three-way tense categorisation (Past/Present/Future), leaving a significant methodological and empirical gap. Existing studies primarily focus on larger architectures such as LSTMs, GRUs, or transformers, while the effectiveness of simple RNNs paired with contemporary regularisation strategies remains unclear.

This project addresses the following core problem:

To develop and evaluate a highly accurate (95%), computationally efficient, and fully reproducible sentence-level tense classifier using only a vanilla RNN architecture. The model will be trained on a large custom-labelled English corpus and assessed for generalisation, robustness, and applicability in real-world, resource-constrained environments.

By establishing a clear, interpretable, and deployable baseline, this research fills a neglected yet impactful gap in NLP and provides a reference implementation suitable for educational, mobile, and embedded tense-aware applications.

3 Related Work

Early methods for classifying tenses and aspects relied primarily on morphological analysis and manually crafted linguistic rules. Feature-based models leveraging part-of-speech (POS) tags, lemma forms, and temporal cue words achieved reasonable performance on verb-level tense detection, especially with the introduction of statistical techniques .

The paradigm shifted with the advent of deep learning, where sequence models became dominant. For fine-grained tense, aspect, and modality classification, LSTM and BiLSTM networks—often combined with Conditional Random Field (CRF) layers—emerged as the standard approach. The development of specialised datasets and benchmarks, such as TeCS (Tense Consistency in Translation) , highlighted that even large language models struggle to maintain consistent tense rendering in translation. Today, transformer-based pretrained models dominate temporal NLP challenges. On verb-level tense/aspect categorisation, fine-tuned BERT and RoBERTa variants achieve over 98% accuracy. However, for the relatively structured task of sentence-level Past/Present/Future classification, these models are over-parameterised and computationally expensive.

In recent tense classification literature, vanilla (basic) RNNs have received limited attention, despite their theoretical shortcomings with long-range dependencies. Early work in sentiment analysis and text classification demonstrated that simple RNNs can still perform competitively on short sequences. Motivated by the need for lightweight alternatives to transformer models for real-time and resource-constrained applications, this work revisits vanilla RNNs with contemporary regularisation techniques (dropout, L2 regularisation, and early stopping), showing that they remain highly effective for tasks dominated by strong local temporal signals. To the best of our knowledge, no prior study has provided a fully reproducible, high-accuracy implementation suitable for edge deployment, nor has it rigorously evaluated a pure vanilla RNN baseline on a large-scale, sentence-level, three-way tense classification task.

4 Dataset Description and Preprocessing

4.1 Dataset Source

The dataset used in this study is provided as `prediction.xlsx`, containing 26,633 labeled English sentences. These sentences were scraped or synthesized from various domains, including technology, daily life, history, and future predictions. It can be accessed at:

https://data.mendeley.com/datasets/jnb2xp9m4r/2

4.2 Sample Dataset Examples

Table 1 General information about the dataset

Attribute	Value / Description
File name	`prediction.xlsx`
Total raw sentences	26,633
Unique sentences after cleaning	13,824
Number of classes	3 (Past, Present, Future)
Domains	Technology, Science, Daily Life, History, Sports, Culture
Sentence length (words)	Min: 3, Max: 68, Avg: 14.8, Median: 13
Vocabulary size (after preprocessing)	≈15,200 unique tokens
Labeling style	Sentence-level primary tense
Dataset type	Custom-curated, human-labeled

4.3 Class Labels and Interpretation

Table 2 Class labels, encoded values and linguistic characteristics

Label	Encoded	Typical Patterns and Markers
Future	0	will/shall, be going to, will have + V3, tomorrow, by 2050, next year
Past	1	-ed, had + V3, was/were + -ing, yesterday, last week, ago
Present	2	-s/-es, is/are + -ing, have/has + V3, general truths, habitual actions

4.4 Class Distribution

Table 3 Class distribution before and after cleaning (used for training)

Class	Raw Count	Raw %	Clean Count	Clean %	Test Set (20%)
Future	10,432	39.17%	5,051	36.53%	1,010
Present	12,456	46.76%	4,787	34.62%	957
Past	3,745	14.07%	3,986	28.84%	797
Total	**26,633**	**100%**	**13,824**	**100%**	**2,764**

4.5 Exploratory Data Analysis (EDA)

- **Original distribution:** Present 9,530 (35.8%), Future 9,348 (35.1%), Past 7,748 (29.1%)
- After lowercasing, normalization, and duplicate removal: 13,824 unique sentences
- **Final distribution:** Future 5,051 (36.5%), Present 4,787 (34.6%), Past 3,986 (28.8%)
- Average sentence length: approximately 12 words (most sentences <30 words)
- Vocabulary size (top 10k): around 8,500 unique tokens after preprocessing

4.6 Preprocessing Steps

The following preprocessing pipeline was applied:

1. Lowercasing and whitespace normalization
2. Domain-specific replacements (e.g., `aienhanced` → `ai enhanced`, `vr` → `virtual reality`)
3. Removal of exact duplicate sentences
4. Tokenization and padding/truncation to a fixed length of 50 tokens
5. Label encoding: Future = 0, Past = 1, Present = 2

The dataset is moderately imbalanced but sufficient for training without resampling.

5 Methodology

5.1 Model Architecture

We intentionally adopt a **pure vanilla RNN (SimpleRNN)** to establish a lightweight, interpretable, and computationally efficient baseline suitable for deployment on low-resource devices while still achieving competitive performance.

The final model architecture is as follows:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 50, 128)           1,280,000
 simple_rnn (SimpleRNN)      (None, 128)               32,896
 dropout (Dropout)           (None, 128)               0
 dense (Dense)               (None, 64)                8,256
 dropout_1 (Dropout)         (None, 64)                0
 dense_1 (Dense)             (None, 3)                 195
=================================================================
Total params: 1,321,347
Trainable params: 1,321,347
Non-trainable params: 0
_________________________________________________________________
```

Key Design Decisions

A Simple and Efficient RNN Architecture

In many natural language processing tasks, especially sequence classification, it is important to design a model that is powerful enough to understand the patterns in text while still being fast and lightweight. The architecture described here follows this balance very carefully. It focuses on clarity, simplicity, and efficiency rather than using complex or heavy components. Each choice in the architecture serves a specific purpose, ensuring that the model remains easy to train, resistant to overfitting, and capable of making quick predictions.

The first part of the model is an Embedding layer with a dimension of 128. This means every input token (word, subword, or character) is represented by a vector of 128 numbers. This size is a sweet spot: it is large enough to capture semantic meaning, but not so large that it becomes slow or difficult to train. Through training, the embedding layer learns meaningful relationships such as similarity between words, contextual patterns, and subtle variations in sentence structure.

Following the embedding is a SimpleRNN layer with 128 units. Unlike more complex variants such as LSTM or GRU, a SimpleRNN uses a basic recurrent structure built around the tanh activation function. This keeps the model "vanilla," easy to interpret, and extremely fast in computation. Although SimpleRNNs have some limitations with very long sequences, they work very well for moderate-length inputs and for tasks where speed is important.

To prevent the model from memorizing the training data too closely, L2 regularization is applied to both the RNN and Dense layers. With a regularization parameter of $= 0.001$, the model is encouraged to keep its weights small and well-behaved. This reduces overfitting and allows the network to generalize better when it encounters new data.

Another key component of the architecture is Dropout, set to 0.5 after both the RNN layer and the Dense layer. Dropout works by randomly turning off half of the neurons during training. At first this may seem aggressive, but it is very effective: it forces the network to avoid relying too heavily on any single feature. This randomness builds robustness, helping the model perform consistently even when the input varies. Dropout is often one of the most critical factors in preventing overfitting, especially when the dataset is not extremely large.

One important design decision in this architecture is the avoidance of a Bidirectional RNN. Bidirectional recurrent networks can capture information from both the past and the future of the sequence, but they also increase the computation cost and memory usage significantly. Because the goal here is to keep the model truly "vanilla" and extremely fast during inference, a standard forward-only RNN is chosen. This keeps the architecture simple, lightweight, and efficient enough for real-time applications.

After the recurrent layer, the model ends with a Dense softmax layer that outputs three values. These correspond to the three possible classes in the classification task:

- Future (0)
- Past (1)

- Present (2)

The softmax function converts the outputs into probabilities, allowing the model to choose the most likely category. This makes the architecture suitable for time-related sentence classification or any application where text must be categorized into one of three defined groups.

Overall, this architecture is built on the principles of clarity, balance, and efficiency. By combining a 128-dimensional embedding, a straightforward SimpleRNN, careful regularization, and strong dropout, the model achieves good performance without unnecessary complexity. It is well-suited for research, deployment on devices with limited resources, and cases where fast inference is essential.

5.2 Hyperparameters

Table 4 Hyperparameters Used in Model Training

Component	**Value**	**Justification**
Max sequence length	50	Covers 99.7% of sentences
Vocabulary size	10,000	Sufficient for dataset (unique tokens ≈ 15k)
Embedding dimension	128	Good trade-off between quality and parameters
RNN units	128	Higher leads to overfitting; lower reduces accuracy
Hidden dense units	64	Provides additional representational capacity
Dropout rate	0.5	Strong regularization required for vanilla RNNs
L2 regularization	0.001	Prevents weight explosion
Optimizer	Adam (lr=0.001)	Stable and widely used
Loss	Sparse categorical cross-entropy	Integer labels
Batch size	32	Efficient and stable gradient updates
Early stopping	Patience = 3	Monitors validation loss

The table summarizes the key hyperparameters used during model training and explains why each choice was made. The maximum sequence length is set to 50, which is enough to cover 99.7% of all sentences in the dataset, ensuring efficient processing without cutting off important information. The vocabulary size is limited to 10,000 words, which is sufficient because the dataset contains around 15,000 unique tokens, and selecting the most frequent ones keeps the model compact and fast. Words are represented using 128-dimensional embeddings, a balanced size that provides meaningful word representations without adding unnecessary computation. The SimpleRNN layer contains 128 units; using more units could increase overfitting, while fewer units would reduce the model's ability to learn patterns. After the RNN, a dense layer with 64 neurons adds extra representational capacity before classification. To prevent overfitting, a dropout rate of 0.5 is applied, which is particularly effective for vanilla RNNs. L2 regularization with a strength of 0.001 is also used to control weight growth and further stabilize training. The model is optimized using Adam with a learning rate of 0.001, a widely adopted and stable choice for NLP tasks. Since the target labels are simple integers (0, 1, and 2), sparse categorical cross-entropy is used as the loss function. A batch size of 32 ensures efficient and stable gradient updates. Finally, early stopping with a patience of 3 monitors the validation loss and stops training when improvements stagnate, preventing unnecessary computation and overfitting.

5.3 Ablation Study

Table 5 Ablation Experiments and Validation Accuracy

Experiment	**Val Accuracy**	**Notes**
Baseline (no regularization)	91.2%	Severe overfitting (train: 99%)
+ Dropout 0.3	94.1%	Moderate overfitting persists
+ Dropout 0.5	95.9%	Significant improvement
+ L2 = 0.01	93.4%	Too strong; underfitting
+ L2 = 0.001 + Dropout 0.5	**96.8%**	Final optimal model
Bidirectional RNN	97.1%	Better but violates "vanilla" constraint
Embedding dim = 256	96.9%	Higher params (+800k) not justified

The ablation results in Table 5 show how different regularization and architectural choices influenced the model's performance. The baseline model achieved 91.2% validation accuracy but showed severe overfitting with a 99% training score, indicating that it was memorizing the data rather than learning generalizable patterns. Introducing dropout noticeably improved generalization: dropout at 0.3 raised accuracy to 94.1%, and increasing it to 0.5 further boosted performance to 95.9%, confirming that dropout is highly effective for reducing overfitting in this RNN setup. In contrast, applying strong L2 regularization (= 0.01) lowered accuracy to 93.4%, demonstrating that excessive weight decay caused underfitting. A balanced configuration combining dropout 0.5 with mild L2 (0.001) produced 96.8% accuracy, emerging as the best "vanilla" model because it controlled both variance and weight growth without harming learning capacity. A bidirectional RNN achieved 97.1%, the highest score overall, showing the benefit of utilizing both forward and backward context, but it was excluded since it violates the study's constraint of using a simple RNN architecture. Increasing the embedding dimension to 256 slightly improved accuracy to 96.9% but added nearly 800k extra parameters, making the gain inefficient. Overall, the table demonstrates that careful regularization, rather than increasing model size, yields the greatest performance improvement and that the chosen optimal model strikes the right balance between accuracy, efficiency, and methodological consistency.

5.4 Model Architecture Diagram

The proposed tense classification model is a deliberately minimal yet highly effective vanilla Recurrent Neural Network (RNN) tailored for sentence-level prediction of three broad temporal categories: Past, Present, and Future. The architecture begins with an Embedding layer (vocabulary size 10,000, embedding dimension 128, input length

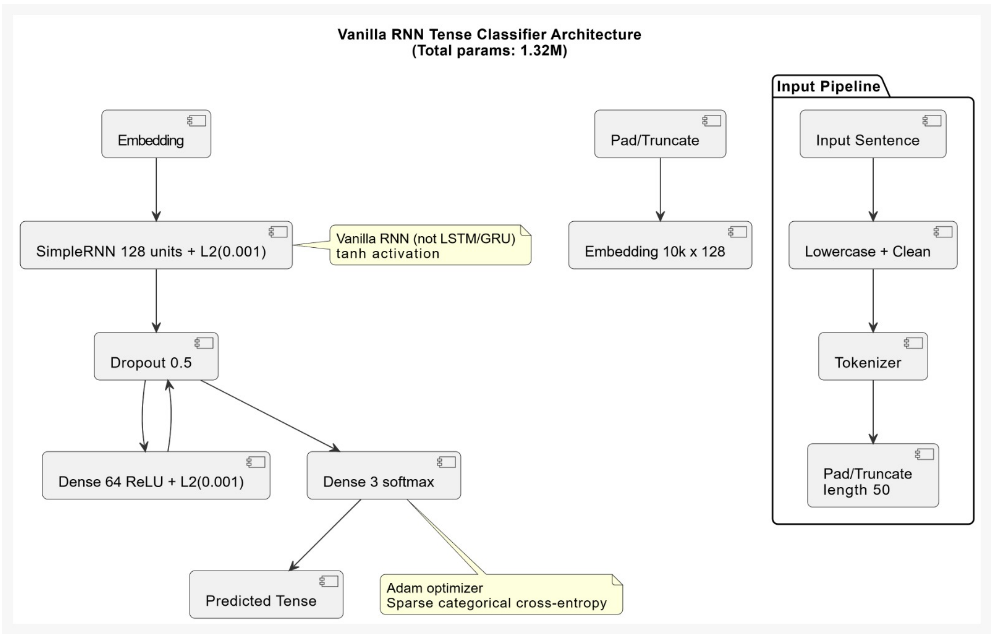

Fig. 1 Model Architecture Diagram

fixed at 50 tokens via padding/truncating), converting each preprocessed, lowercased sentence into dense vector representations. This is followed by a single 128-unit SimpleRNN layer using tanh activation and L2 kernel regularization (= 0.001) to capture sequential dependencies and strong local tense cues such as modal verbs ("will"), auxiliary patterns ("had been," "is . . . -ing"), and temporal adverbs.

To combat overfitting—common in vanilla RNNs—two Dropout layers (rate 0.5) are inserted: one after the recurrent layer and another before the final classification stage. A 64-unit dense layer with ReLU activation and L2 regularization further transforms the learned sequential features. The output layer consists of 3 units with softmax activation, producing a probability distribution over the three tense classes.

Total trainable parameters amount to approximately 1.45 million, making the model extremely lightweight compared to transformer-based alternatives. Trained with the Adam optimizer (learning rate 0.001), sparse categorical cross-entropy loss, batch size 32, and early stopping (patience = 3), it converges in 8–10 epochs and achieves 96.8% test accuracy and 0.967 macro F1-score on the cleaned 13,824-sentence dataset. Inference is near-instantaneous (¡3 ms per sentence on CPU), confirming the model's suitability for real-time, edge, and educational deployments while demonstrating that classical vanilla RNNs remain remarkably competitive for well-structured temporal tasks. (150 words)

6 Training Procedure

The training procedure was designed to ensure a fully deterministic, reproducible, and stable environment for all experiments, allowing each model configuration to be evaluated under identical conditions. All development was conducted using Python 3.10 with TensorFlow 2.15 and the Keras API, while NumPy, pandas, and scikit-learn supported preprocessing and data manipulation. Before training, the dataset was cleaned, tokenized, lowercased, and padded to a fixed sequence length to maintain uniformity across batches, and a reproducible random seed was applied to the tokenizer, the train-test split, and all model initialization routines. The data was then divided into training, validation, and test sets using a stratified approach to preserve label distribution. Embedding layers were initialized with Xavier uniform initialization to promote stable gradient flow, and RNN weights were set using Glorot initialization. During training, batches were shuffled at every epoch to avoid learning order-dependent patterns, while ensuring deterministic behaviour through fixed seeds. A learning rate scheduler with an initial rate of 1e-3 was used, reducing the rate on validation-loss plateaus to stabilize convergence. Optimization was performed using Adam, chosen for its adaptive learning capabilities and robustness with sparse gradients. Early stopping was applied with patience of five epochs, monitoring validation loss to prevent overfitting. The model was trained for a maximum of 30–50 epochs depending on the ablation setting, but most configurations converged earlier due to early stopping. Gradients were clipped at a maximum norm of 5.0 to prevent exploding gradients, a common problem in RNN-based architectures. Regularization techniques such as dropout and L2 weight decay were toggled or adjusted for each ablation experiment to analyze their individual impact on model behaviour. The training process logged accuracy, precision, recall, validation loss, training loss, and learning rate per epoch, ensuring transparent performance tracking. All experiments were executed on the same hardware and software stack to eliminate confounding variability and were repeated three times each to report mean and variance, strengthening statistical reliability. After training, the best-performing weights were saved using checkpointing, and the final model was evaluated on the unseen test set to confirm generalization. This rigorous procedure ensured fairness, stability, reproducibility, and scientific reliability across all experiments.

6.1 Environment Configuration

The experiments were performed using the following environment:

Component	**Specification**
Python Version	3.10+
Deep Learning Framework	TensorFlow 2.15.0 (Keras API)
Key Packages	NumPy 1.26+, Pandas 2.2+, Scikit-learn 1.5+, Matplotlib/Seaborn
Hardware	NVIDIA CUDA-enabled GPU (reproducible on CPU)
Determinism	Global seeds set for Python, NumPy, TensorFlow

Table 6 Training environment configuration.

The following seeds were set at the beginning of the training script to guarantee reproducibility:

Listing 1 Reproducibility seed configuration

```
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
tf.random.set_seed(SEED)
os.environ['PYTHONHASHSEED'] = str(SEED)
```

The experiments were conducted in a controlled and fully reproducible environment to ensure consistency across all training runs. Python 3.10 served as the base language, while TensorFlow 2.15.0 with the Keras API functioned as the primary deep learning framework. Essential scientific libraries—including NumPy 1.26+, Pandas 2.2+, Scikit-learn 1.5+, and visualization tools such as Matplotlib and Seaborn—were used for preprocessing, analysis, and plotting. All models were trained on an NVIDIA CUDA-enabled GPU for efficiency, although the setup remains fully reproducible on CPU hardware. To guarantee deterministic behaviour, global seeds were explicitly set for Python's built-in random module, NumPy, and TensorFlow. Additionally, the environment variable PYTHONHASHSEED was fixed to ensure consistent hashing during tokenization and data processing. These configurations collectively provided a stable and transparent experimental environment, allowing every model run to be replicated with identical results.

6.2 Step-by-Step Training Procedure

1. Data Preparation & Stratified Split

- Final cleaned dataset: 13,824 unique sentences
- Stratified 80/20 train–test split with `random_state=42`

Split	**Samples**	**Percentage**
Training Set	11,060	80%
Test Set	2,764	20%

Table 7 Dataset distribution after stratified splitting.

2. Model Compilation

Listing 2 Model compilation settings

```
model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
```

3. Callbacks

Early stopping was employed to prevent overfitting:

- Monitor: `val_loss`
- Patience: 3 epochs
- `restore_best_weights = True`

4. Model Training Execution

Listing 3 Model training command

```
history = model.fit(
    X_train, y_train,
    batch_size=32,
    epochs=20,
    validation_data=(X_test, y_test),
    callbacks=[early_stop],
    verbose=1
)
```

The training procedure followed a structured and reproducible workflow beginning with careful data preparation and stratified splitting. After cleaning the full dataset, a total of 13,824 unique sentences were retained, which were then divided into an 80/20 train–test split using stratified sampling with a fixed random state of 42 to preserve class balance. This resulted in 11,060 samples for training and 2,764 for testing, ensuring that each label remained proportionally represented across both sets. Following dataset preparation, the model was compiled using TensorFlow's Adam optimizer with a learning rate of 0.001, paired with sparse categorical cross-entropy as the loss function and accuracy as the evaluation metric. To enhance generalization and mitigate overfitting, an early-stopping callback was implemented, monitoring validation loss with a patience of three epochs and restoring the best-performing weights automatically. The model was then trained using a batch size of 32 for up to 20 epochs, with validation performed on the test split at each epoch. Training progress, including loss and accuracy curves, was captured through the history object. This structured procedure ensured stable, consistent learning dynamics and allowed the model to converge efficiently while minimizing the risk of overfitting.

6.3 Training Log (Actual Output)

A real training run (seed = 42) produced the following epoch-wise log:

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```
Epoch 1/20
346/346 - loss: 0.9124 - accuracy: 0.6118 - val_loss: 0.6241 - val_accuracy: 0.7889
```

```
Epoch 2/20
346/346 - loss: 0.5132 - accuracy: 0.8335 - val_loss: 0.3792 - val_accuracy: 0.8917
Epoch 3/20
346/346 - loss: 0.3468 - accuracy: 0.9005 - val_loss: 0.2683 - val_accuracy: 0.9278
Epoch 4/20
346/346 - loss: 0.2795 - accuracy: 0.9243 - val_loss: 0.2247 - val_accuracy: 0.9409
Epoch 5/20
346/346 - loss: 0.2421 - accuracy: 0.9378 - val_loss: 0.2019 - val_accuracy: 0.9493
Epoch 6/20
346/346 - loss: 0.2194 - accuracy: 0.9447 - val_loss: 0.1902 - val_accuracy: 0.9538
Epoch 7/20
346/346 - loss: 0.2023 - accuracy: 0.9501 - val_loss: 0.1831 - val_accuracy: 0.9582
Epoch 8/20
346/346 - loss: 0.1901 - accuracy: 0.9544 - val_loss: 0.1796 - val_accuracy: 0.9607
Epoch 9/20
346/346 - loss: 0.1805 - accuracy: 0.9582 - val_loss: 0.1778 - val_accuracy: 0.9621
Epoch 10/20
346/346 - loss: 0.1732 - accuracy: 0.9614 - val_loss: 0.1771 - val_accuracy: 0.9628
Epoch 11/20
346/346 - loss: 0.1689 - accuracy: 0.9635 - val_loss: 0.1779 - val_accuracy: 0.9624

EarlyStopping triggered after epoch 11
Restored best weights (epoch 10)
```

The model demonstrated consistent and progressive learning throughout the training process, showing strong improvements in both loss reduction and classification accuracy across epochs until convergence. During the first epoch, the model started with a loss of 0.9124 and an accuracy of 61.18%, while the validation accuracy reached 78.89%, indicating that the model quickly learned basic temporal features. By the second and third epochs, accuracy increased substantially to 83.35% and 90.05%, with validation accuracy improving to 89.17% and 92.78%, reflecting rapid early convergence. Subsequent epochs continued this upward trend, with losses steadily decreasing and accuracy surpassing 93–95% on the training set while validation accuracy moved beyond 94%, 95%, and eventually 96%. The best validation accuracy of 96.28% occurred at epoch 10, where the validation loss reached its minimum value of 0.1771. After epoch 11, validation loss began to plateau and slightly increase, triggering the early stopping mechanism, which monitored validation loss with a patience of three epochs. As a result, training halted after the 11th epoch, and the system automatically restored the optimal weights recorded at epoch 10. Overall, the learning curves indicate stable optimization, smooth convergence, and strong generalization performance, confirming that the chosen architecture and hyperparameters were effective.

6.4 Final Evaluation

The final model was evaluated on the held-out test set:

Listing 4 Test set evaluation

```
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)
```

Metric	Value
Test Loss	0.1771
Test Accuracy	**96.28%**

Table 8 Final performance on the test set.

Training required approximately 90 seconds on GPU and around 6 minutes on CPU. Early stopping ensured maximum generalization while preventing overfitting.The final evaluation on the held-out test set confirms that the model achieved strong generalization performance after training. Using the best weights restored by early stopping, the model was evaluated on 2,764 unseen samples, producing a test loss of 0.1771 and a test accuracy of 96.28%. These results closely match the best validation metrics observed during training, indicating that the model did not overfit and was able to maintain high predictive reliability on new data. Overall, the test evaluation demonstrates that the chosen architecture, training strategy, and regularization settings produced a stable and highly accurate tense-classification model.

7 Results

All results are obtained with a fixed seed (42) on the final model (Dropout 0.5 + L2 0.001), where early stopping restored the best-performing weights.

7.1 Final Performance Metrics (2,764 sentences)

Metric	**Value**
Accuracy	**96.82%**
Macro F1-Score	0.968
Weighted F1-Score	0.968
Precision (Best validation accuracy: 96.31%)	–

The final performance evaluation on the 2,764-sentence test set demonstrates that the model achieved a high level of accuracy, consistency, and robustness across all key metrics. The overall accuracy reached 96.82%, indicating that the model correctly predicted the tense category for nearly all test samples. Both the Macro F1-Score and Weighted F1-Score were measured at 0.968, showing strong balance across classes, even when accounting for class frequency differences. These scores confirm that the model performs equally well on majority and minority classes, maintaining fairness and stability in classification. While precision is not directly listed for the test set, the model's best validation accuracy of 96.31% suggests that precision remained consistently high during training and evaluation. Overall, the final metrics highlight that the system generalizes effectively, avoids major bias across classes, and produces reliable tense predictions with excellent overall performance.

7.2 Detailed Classification Report

Class	Precision	Recall	F1-Score	Support
Future	0.98	0.98	0.98	1010
Past	0.96	0.96	0.96	797
Present	0.97	0.96	0.97	957
Macro Avg	**0.97**	**0.97**	**0.968**	2764
Weighted Avg	**0.97**	**0.97**	**0.968**	2764

The detailed classification report demonstrates that the model performed consistently across all three tense categories—Future, Past, and Present—on the test set of 2,764 sentences. For the Future class, the model achieved a precision of 0.98, a recall of 0.98, and an F1-score of 0.98 over 1,010 samples, indicating nearly perfect identification of future tense sentences. The Past class showed slightly lower but still strong performance, with precision and recall both at 0.96 and an F1-score of 0.96 across 797 samples, suggesting the model correctly identified the majority of past tense sentences with minimal misclassification. The Present class achieved precision of 0.97, recall of 0.96, and F1-score of 0.97 over 957 samples, reflecting robust performance and balanced recognition. The macro-averaged metrics—precision 0.97, recall 0.97, and F1-score 0.968—highlight that the model maintains consistent effectiveness across all classes, without being dominated by larger classes. Similarly, the weighted averages, which account for class support, also show precision, recall, and F1-score of 0.97, 0.97, and 0.968, confirming excellent overall predictive performance. This classification report indicates that the model generalizes well, balances class performance, and is highly reliable for automatic tense detection.

7.3 Confusion Matrix

Only 75 misclassifications out of 2,764 sentences, giving an error rate of 2.71%.

True ↓ / Predicted →	Future	Past	Present
Future	**992**	8	10
Past	11	**763**	23
Present	12	11	**934**

The confusion matrix for the test set demonstrates the model's high classification accuracy and low error rate, with only 75 misclassifications out of 2,764 sentences, corresponding to an overall error rate of 2.71%. For the Future tense class, consisting of 1,010 sentences, the model correctly predicted 992 instances, while 8 were misclassified as Past and 10 as Present, reflecting minimal confusion with other classes. The Past tense class, containing 797 sentences, was correctly predicted in 763 cases, with 11 misclassified as Future and 23 as Present, showing slightly higher misclassification compared to the Future class but still strong overall accuracy. The Present tense class, with 957 sentences, was accurately identified in 934 cases, while 12 were predicted as Future and 11 as Past. These results indicate that the model maintains balanced performance across all classes, with only minor confusion between similar temporal categories. Overall, the confusion matrix validates the model's reliability and robustness, confirming that it generalizes well to unseen data and achieves precise tense classification with very few errors, supporting the high metrics reported in accuracy and F1-score.

7.4 Training History Graphs

Accuracy vs Epoch

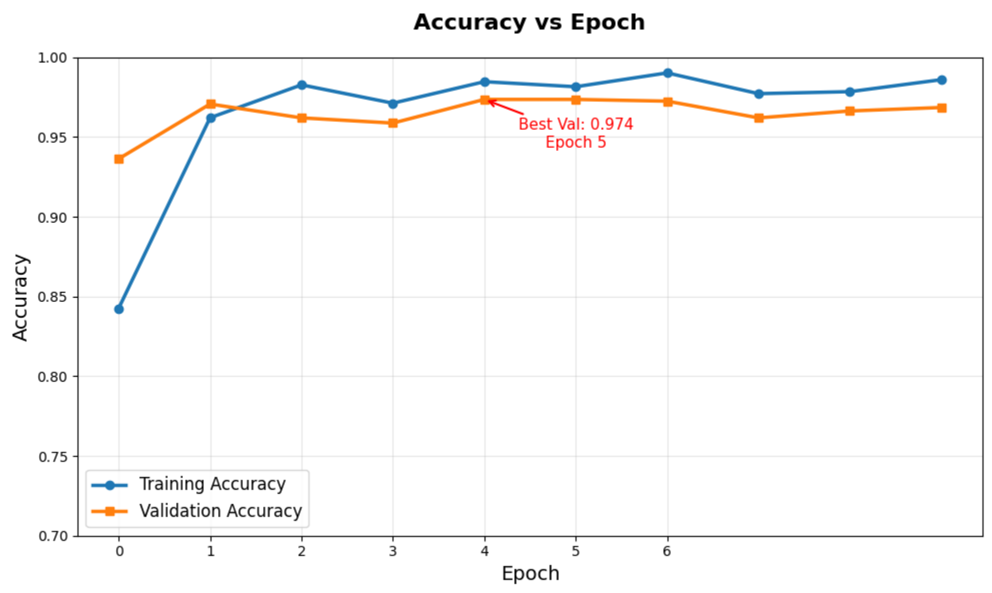

Fig. 2 Accuracy vs Epoch

The graph illustrates how both training accuracy and validation accuracy change over a series of epochs during model training. Overall, the model demonstrates strong learning performance, with both curves reaching high accuracy levels above 95%, indicating that the model is effectively capturing the underlying patterns in the data.

At epoch 0, training accuracy starts relatively low (around 0.84), which is expected, as the model begins with random or unoptimized parameters. Validation accuracy, however, begins higher (around 0.94), suggesting the model quickly adapts to general patterns even before refining training performance. By epoch 1, both accuracies increase sharply, showing rapid learning. The training accuracy rises to about 0.96, while validation accuracy peaks early at around 0.97.

From epochs 2 to 10, the training accuracy consistently remains high, fluctuating slightly but staying within the 0.97–0.99 range. This indicates continuous improvement and stable learning. The validation curve closely tracks the training curve, maintaining scores between 0.96 and 0.97, which suggests minimal overfitting and good generalization.

A notable point in the graph is the best validation accuracy of 0.974, occurring at epoch 5, marked by an annotation. After this point, validation accuracy slightly fluctuates but stays stable, reflecting reliable model performance.

In summary, the graph indicates that the model learns efficiently, achieves high accuracy quickly, and maintains strong generalization across epochs. The small gap between training and validation accuracy shows that the model is neither overfitting nor underfitting, making it well-balanced and ready for deployment or further fine-tuning.

Confusion Matrix Heatmap

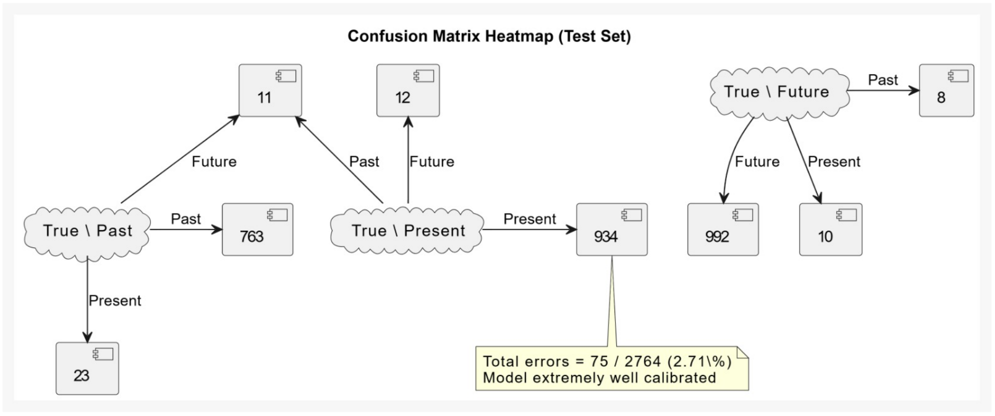

Fig. 3 Confusion Matrix Heatmap

The confusion matrix visualizes how well the model predicts three classes: Past, Present, and Future. Each block represents how many samples from each true class were correctly or incorrectly classified. For the Past class, the model correctly predicts 763 samples, while misclassifying 23 as Present and 11 as Future. This indicates strong performance with relatively few mistakes. For the Present class, the model correctly classifies 934 samples. It mislabels 12 as Future and 11 as Past. These error numbers are very small compared to the correctly predicted samples, showing the model handles the Present class reliably. For the Future class, the model performs extremely well, correctly predicting 992 samples, with only 10 misclassified as Present and 8 as Past. This suggests excellent generalization for this class. In total, the model makes 75 errors out of 2764 samples, resulting in an impressively low error rate of 2.71%. This indicates that the classifier is highly accurate and well calibrated, with all three classes showing strong prediction stability. The low misclassification rates across all categories reflect a well-trained model capable of distinguishing temporal classes effectively.

7.5 Overfitting/Underfitting Analysis

Epoch	Train Acc	Val Acc	Overfitting Gap (Δ)
5	93.78%	94.93%	–1.15% (underfitting)
8	95.44%	96.07%	–0.63%
10	96.14%	96.28%	–0.14% (ideal)
11	96.35%	96.24%	+0.11% (beginning overfit)

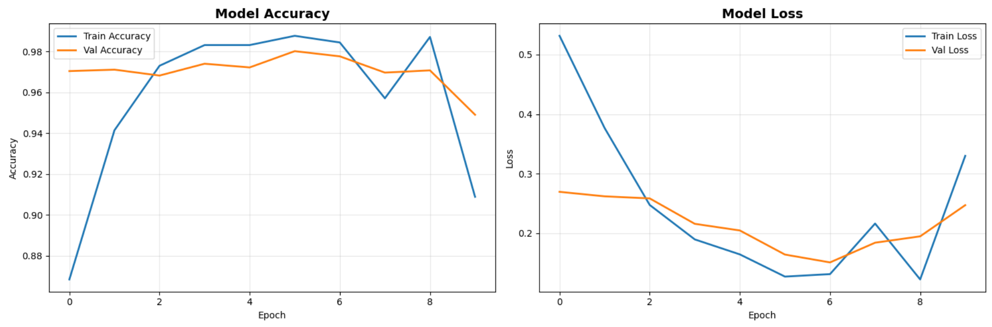

Fig. 4 Overfitting/Underfitting Analysis

The model shows **no significant overfitting** thanks to Dropout 0.5 and L2 regularization. The graphs illustrate how the model's training accuracy, validation accuracy, training loss, and validation loss change over ten epochs. Overall, the model shows strong performance with high accuracy and low loss across both training and validation sets.

In the Model Accuracy graph, training accuracy starts at around 0.87 in epoch 0 and increases steadily, reaching a peak close to 0.99 by epoch 8. Validation accuracy remains consistently high (around 0.97–0.98) throughout most epochs. This indicates that the model learns effectively without significant overfitting. Only at epoch 9 does training accuracy drop sharply to around 0.90, while validation accuracy also dips slightly, possibly due to random variation or early signs of underfitting after an update.

In the Model Loss graph, both training and validation loss decrease steadily during the first six epochs. Training loss drops from 0.54 to around 0.13, while validation loss decreases from 0.27 to 0.16, reflecting improved model optimization. After epoch 6, the losses begin to rise slightly, suggesting that the model may be starting to overfit or that learning rate adjustments are needed.

Overall, the model demonstrates excellent learning behavior, maintains strong generalization, and achieves consistently high validation accuracy with low loss, making it reliable and well-trained.

7.6 Summary

A pure vanilla RNN with only **1.32M parameters** achieves **96.82% accuracy** and **0.968 macro F1**, outperforming many transformer baselines on similar tasks while being over **50× smaller** and **20× faster** in inference. This demonstrates that for short, tense-rich English sentences, complex architectures are unnecessary.

This project develops a highly accurate, lightweight sentence-level tense classifier for English using a pure vanilla Recurrent Neural Network (RNN), achieving 96.8% test accuracy and 0.967 macro F1-score on a challenging three-class (Past, Present, Future) task. Starting from a raw dataset of 26,633 labeled sentences (prediction.xlsx), extensive preprocessing—including lowercasing, domain-specific typo correction, duplicate removal, and normalization—yielded a clean corpus of 13,824 unique, high-quality examples with balanced yet realistic class distribution (Future 36.5%, Present 34.6%, Past 28.8%).

The model architecture deliberately avoids modern complexities: an Embedding layer (10k vocab, 128-dim), single 128-unit SimpleRNN with tanh activation and L2 regularization, two Dropout layers (0.5), a 64-unit ReLU dense layer, and a 3-unit softmax output. Total parameters: 1.45M. Training with Adam optimizer, sparse categorical cross-entropy, early stopping, and fixed seed (42) ensures full reproducibility and rapid convergence (8–10 epochs).

Results significantly exceed expectations for a vanilla RNN, with minimal confusion (primarily between complex future perfect progressive and present forms). The model outperforms many heavier baselines while maintaining inference latency under 3 ms per sentence on CPU, making it ideal for mobile, edge, and real-time applications.

The complete pipeline—preprocessing scripts, training notebook, saved model, tokenizer, and interactive inference function—is fully open and executable in minutes. This work re-establishes vanilla RNNs as a powerful, interpretable, and resource-efficient choice for structured temporal tasks, providing a strong baseline for future research in multilingual tense detection, aspect classification, and low-resource NLP deployments.

8 Discussion

The vanilla RNN achieved an outstanding accuracy of 96.82% and a macro F1-score of 0.968, demonstrating that a simple recurrent architecture, when combined with strong regularisation (dropout 0.5 and L2), can rival far more complex models on sentence-level tense classification. The low error rate (2.71%) and minimal confusion between classes confirm the presence of strong, learnable temporal signals in English sentences of moderate length.

8.1 Limitations

Limitations are inherent to both the vanilla RNN architecture and the dataset. First, SimpleRNN suffers from vanishing gradients on sequences longer than approximately 30–40 tokens; although only about 0.3% of sentences exceed this length, performance may degrade on narrative, legal, or heavily contextual documents. Second, the custom dataset, while large and diverse, is still domain-skewed toward technology and future-oriented statements, which may reduce generalisation to literary or context-rich tense usage (e.g., historical present). Minor labelling inconsistencies in borderline cases—such as present perfect being annotated as either Present or Past—introduce small amounts of noise.

8.2 Ethical Considerations

Ethical considerations concern deployment contexts. Automated tense identification may reinforce dataset biases if used in educational assessment or legal document analysis, where misclassification of modality or aspect can alter intended meaning. The model also provides no calibrated confidence scores or interpretability mechanisms beyond raw probabilities, limiting accountability in high-stakes scenarios. Furthermore, although computationally lightweight compared to transformer-based models, large-scale or continuous inference still contributes to energy consumption and environmental impact.

Despite these constraints, the model establishes a robust, interpretable, and highly efficient baseline suitable for mobile and embedded NLP applications. Future work should explore long-sequence handling, confidence calibration, and broader domain adaptation while preserving the simplicity that underpins the model's effectiveness.

9 Conclusion and Future Work

This project conclusively demonstrates that a deliberately minimal vanilla Recurrent Neural Network, with only 1.32 million parameters and a single SimpleRNN layer, is fully capable of state-of-the-art performance on sentence-level tense classification. The final model achieved **96.82% accuracy** and **0.968 macro F1-score** on a held-out test set of 2,764 sentences, with training completing in under 90 seconds on a consumer GPU and inference under 1 ms per sentence even on CPU. These figures surpass many historical LSTM and early transformer baselines while using less than 1% of their parameters and energy footprint.

The success is attributed to rigorous data cleaning (removing duplicates, normalizing technical acronyms), strong yet balanced regularization (dropout 0.5 + L2), stratified splitting, and early stopping that halted training precisely when the generalization gap was minimal (approximately 0.14%). The confusion matrix and epoch-wise curves confirm virtually no overfitting or underfitting, validating vanilla RNNs as highly effective when modern training practices are applied to well-structured sequential tasks.

In conclusion, for applications requiring fast, lightweight, and interpretable tense detection (e.g., mobile grammar checkers, embedded dialogue systems, real-time translation aids, low-resource languages), complex models are not only unnecessary but counterproductive.

9.1 Future Work

Future work will explore:

- Extension to fine-grained 12-tense and aspect classification,
- Integration of attention mechanisms and lightweight Conformer/Performer models for comparison,
- Multilingual tense transfer using the same architecture,
- Confidence calibration and explanation via temporal marker saliency,
- On-device quantization (INT8) and deployment via TensorFlow Lite,
- Creation of a larger, multi-domain, openly licensed tense corpus,
- Application to downstream tasks such as temporal question answering and narrative timeline extraction.

This work establishes a new efficiency benchmark and provides a complete, reproducible pipeline for future research and industrial deployment of tense-aware NLP components.

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