



## RESEARCH ARTICLE

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# CUSTOM LOSS FUNCTIONS TO TACKLE CLASS IMBALANCE, ENHANCE SPECIFIC PERFORMANCE MEASURE, AND IMPROVE CLASSIFICATION PERFORMANCE IN THE CONTEXT OF FAKE NEWS DETECTION

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## ABSTRACT

The spread of false information on social media has raised serious concerns across the globe. Most social media contents are multimodal, comprising text, images, and substantial data generated through likes, tweets, retweets, and replies. To address this challenge, a hierarchical deep learning model that learns and fuses features from each modality is necessary. In the literature, early and decision level fusion inspired hierarchical deep learning multimodal models are designed for fake news detection. However, these models rely solely on cross-entropy loss, which is insufficient given the real-world, imbalanced nature of fake news datasets. Additionally, decision-level fusion models present simplified architectures but they cannot effectively handle the complexities of multimodal data resulting in less accurate models. In this work, we address the mentioned issues by introducing custom loss functions specific to early and decision level fusion multimodal deep learning models. Three different loss functions namely: Adaptive Hybrid Loss (AHL), False Negative based loss (FNL) and Similarity preserving loss (SPL) are designed. The proposed loss functions combine the benefits of focal loss and cross-entropy loss. AHL is suitable for the problems where achieving precision and recall are equally important, FNL is used in case where recall is more important as in case of Fake news detection. SPL provides balance between precision and accuracy and improves the detection accuracy. On Fake news net dataset AHL provides a F1 score of 92.36% and FNL provides improved recall of 93.18% and SPL provides F1 score of 90.26% which is higher than the models trained using cross entropy loss. Our experimental results demonstrate that these tailored loss functions significantly boost the performance of multimodal fake news detection (FND) systems, providing a comprehensive solution for combating misinformation in the digital age.



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## I. INTRODUCTION

Fake news detection has become a major challenge in today's society. The widespread use of social media platforms has fundamentally transformed how people consume information. Unlike traditional news sources, which typically involve some degree of editorial oversight, social media allows anyone to publish and disseminate content. Although this democratization of information sharing has advantages, it also makes it easier for false information and fake news to proliferate quickly. In recent years, the consequences of fake news have continued to escalate, impacting various sectors globally. For instance, during the COVID-19 pandemic, false information spread about treatments and vaccines which fueled fear and confusion among people [1], 2020 U.S. presidential election, false information was widely circulated, including baseless claims of widespread voter fraud resulting in riots [2]. The trust that individuals place in social media content is significantly influenced by the engagement metrics of that content. When users encounter news stories, articles, or posts that have substantial number of likes, shares, and comments, their perception of the content's credibility often increases.

This phenomenon, known as the "bandwagon effect," [3] suggests that people are more likely to believe information that appears to be widely accepted by others. As a result, fake news stories that become popular create a false sense of legitimacy, leading to widespread acceptance and further propagation. This trust in social media content is particularly problematic when the content in question is false or misleading. Fake news can have major implications, such as affecting public opinion, swaying elections, or ignite violence. False information can spread quickly and extensively on social media, making it difficult to manage and prevent. Addressing the spread of fake news requires sophisticated methods for detection and verification. AI researchers have been at the forefront of this effort, developing advanced techniques to recognize and lessen the effect of fake news. These techniques primarily focus on deep learning models with two approaches: Early fusion Approach: This approach involves creating a unified model that integrates features from various modalities, such as text, images, and social context data (likes, shares, and comments) and generating a shared feature representation. The generated feature vector has all the relevant information from different modalities. Decision level **or Ensemble Approach**: In this method, independent models are designed for each modality, and their predictions are combined to make a final decision. This ensemble technique benefits from the diverse strengths of multiple models, aiming to provide a more robust and accurate overall prediction. Each model specializes in a different aspect of the data, and their collective output is used to determine the veracity of the content.

A significant challenge in training and validating such models is the nature of the available datasets. These datasets are often derived from real-world sources like online news websites and social media platforms and exhibit a natural imbalance between fake and real news samples. For example, real samples significantly outnumber fake news samples in many datasets. Typical loss functions, such as Cross-Entropy (CE) loss, underperform due to this class imbalance [4]. This imbalance causes deep learning models to focus on learning features of the majority class (real news) while neglecting the minority class (fake news). As a result, models become biased towards predicting real news, leading to poor detection of fake news, since they lack sufficient samples to learn distinctive features of fake news. Accuracy, thus becomes an insufficient performance measure. Instead, more focus is required on metrics that address specific problem requirement. For example, recall is important in fake news detection. The rate of false negatives instances where fake news is misclassified as real are errors and it should be heavily penalized to improve the reliability of the detection system. Therefore, it is crucial to design loss functions that heavily penalize false negatives, ensuring that models are more sensitive to detecting fake news.

Furthermore, ensemble models often fall short of achieving the desired accuracy because they are trained independently and fail to capture the correlations between different modalities. Typically, predictions are combined using methods such as max, average, or weighted average. These approaches may not yield accurate results when there is significant variation in the predictions. Therefore, efforts should be directed towards ensuring that the model cohesively learns features, promoting consistency and similarity in the predictions. Hence Fake news detection has become a global challenge in the digital age with the proliferation of misinformation on social media. While several deep learning models have been proposed, may fail to address the significant issue of class imbalance in real world datasets, where real news often outnumbers fake news. This study proposes novel custom loss functions to enhance multimodal fake news detection by focusing on target specific learning and addressing class imbalance. These loss functions improve the precision and recall of models offering an accurate solution to the problem of fake news detection across different datasets. The major contributions of this work include:

1. End-to-end multimodal Deep Learning Systems with personalized loss functions tailored to improve fake news detection.
2. In the context of Fake News Detection, this is one-of-a-kind approach which addresses class imbalance problem and performs target-specific learning.
3. Three Novel Loss Functions namely AHL, FNL and SPL are designed that addresses the class imbalance problem, perform problem specific learning and enhance the accuracy.
4. A thorough comparative analysis of the proposed loss functions against other existing loss functions in the literature is presented.
5. The generalizability of designed loss functions is demonstrated, by evaluating its performance on two other real-world datasets: Fake Edit and Twitter Mediaeval.

The rest of the paper is organized as follows: Section 2 discusses related work, Section 3 outlines the proposed methods, detailing the two end-to-end deep learning models, the formulas and mathematical modelling of the proposed loss functions. Section 4 covers the experimental details, followed by result analysis. Section 5 provides the conclusion and future scope.

## II. RELATED WORKS

By [5] provides an extensive review of cutting-edge deep learning (DL) techniques for multimodal fake news detection, underscoring the importance of this problem at both individual and societal levels. The authors highlight various DL models, including discriminative models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), and generative models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). The review also identifies several open issues and challenges, such as data imbalance, effective feature representation, model interpretability, and generalization across different datasets [5]. Loss functions play a major role in training and optimizing such deep learning models. Two mostly used loss functions in literature are cross entropy loss and focal loss.

### II.1 CROSS ENTROPY LOSS

Deep learning based fake news detection systems mainly use cross entropy loss [6-9]. By [6] fused text and image representations and used a multi-layer perceptron for classification. The total loss of the model is calculated using a cross-entropy loss function. This approach highlights the importance of effectively combining multimodal features to improve the accuracy of fake news detection. In turn [7] focuses on the use of cross-entropy loss as the objective function in fake news detection models.

$$L_{BCE} = -\frac{1}{M} \sum_{i=1}^M (y_i \log y_i^p) + (1 - y_i) \log(1 - y_i^p) \quad (1)$$

Where,

$y_i$  Target label for ith sample.  
 $M$  Total number of samples.  
 $y_i^p$  Prediction for ith sample.

While cross-entropy loss is commonly used and effective in many scenarios, it may not adequately address specific challenges such as data imbalance and the need for penalizing false negatives more heavily.

## II.2 FOCAL LOSS

Focal loss is derived from the cross-entropy loss and is used for addressing class imbalance problems by adding a modulating term. The study [10] have demonstrated the efficacy of Focal Loss in addressing class imbalance by down weighting easy to classify samples. However, its static nature limits the effectiveness when dealing with dynamically changing data distributions during training [11]. The AHL overcomes this limitation by adjusting the weight between Focal loss (FL) and Binary Cross Entropy (BCE) based on current performance of the model. The formula for focal loss is given in equation (2).

$$L_{FL} = -\frac{1}{M} \sum_{i=1}^M (1 - p_i)^\gamma \log p_i \quad (2)$$

Where

$p_i = p_i$  for a majority class and  $p_i = (1 - p_i)$  for a minority class.

## II.3 CUSTOM LOSS FUNCTIONS

Specific to the problem, custom loss functions are designed in literature. By [12] introduces a novel loss function comprising two components. The first component focuses on multimodal fusion, integrating features from different modalities, while the second component considers the similarity between news articles. Weights are assigned to each branch to balance their contributions. This approach aims to enhance the detection accuracy by effectively combining multimodal information and ensuring that similar news articles are treated accordingly. In turn [13] uses autoencoders to learn shared multimodal representations. A reconstruction error is calculated, where posts with high reconstruction errors are considered fake. This method leverages the capability of autoencoders to capture the underlying structure of multimodal data and identify anomalies indicative of fake news. According to [14] presents a method where both labelled and unlabelled news texts are jointly used to train a CNN model. The loss function employed is a sum of cross-entropy and weighted mean squared error. This approach aims to leverage the abundant unlabelled data available online to improve the model's performance and robustness in detecting fake news. By [15] introduces diversity in ensemble learning by adding a Kullback-Leibler (KL) divergence loss. This addition encourages the base learners within the ensemble to make diverse predictions, enhancing the overall robustness and accuracy of the ensemble model. In turn [16] proposes a multimodal loss function that integrates triplet loss and an attention mechanism. This approach aims to improve the model's capacity to concentrate on relevant features across different modalities, thereby improving the accuracy of fake news detection. According to [17] introduced a novel loss function that encourages base learners to focus on important aspects of news articles using an attention mechanism. This method aims to achieve greater accuracy by ensuring that the model pays more attention to critical features indicative of fake news. By [18] discusses the importance of accuracy and diversity factors in making ensemble models more efficient. The authors propose a new diversity-driven loss function that enhances the performance of ensembles by balancing the trade-off between accuracy and diversity among the base learners.

In turn [19] designed a parameter free loss function for class imbalance problem. It modified the CE loss where the class probability for a sample was replaced with the average probability of samples in the mini batch. The proposed loss treats each class equally and gives more consideration to minority class. It is also robust to outliers. By [20] assigned real weights to the CE loss. It used marginal cost as weights. The marginal cost is calculated with respect to false negative, true positive and false positive and true negative. According to [21] designed a Unified Focal loss for addressing class imbalance problem, the designed loss that generalizes Dice and cross entropy-based loss functions. By [22] addressed the class imbalance problem by introducing custom loss function based on every class's mean square error. The loss function, balanced mini batch approach and real time data augmentation together are used to tackle the class imbalance in skin cancer detection. In context of Fake news detection systems, significant progress has been made in developing advanced deep learning models, but little works focus on designing custom hyper parameters such as loss functions specific to problems. Existing models often struggle with the imbalanced nature of fake news datasets, resulting in biased results. For example, models with high false negative rates where fake news is misclassified as real. This is particularly problematic as it allows misinformation to continue spreading. Furthermore, ensemble approaches in fake news detection, where predictions from multiple models are combined, often fail to account for the interdependencies between different modalities. Each base model learns independently, which can result in suboptimal integration of multimodal information. In response to these challenges, our work focuses on designing novel loss functions tailored to the specific requirements of multimodal fake news detection. We propose an AHL function that addresses class imbalance, FN based loss which reduces the impact of false negatives and a similarity-preserving loss function that enhances the accuracy of ensemble models by forcing the model to learn feature such that their predictions are similar. Table 1 presents a summary of custom designed loss functions used in literature.

Table 1: Summary of custom-designed loss functions in literature.

| Reference No. | Loss Description                                                                                                                                      | Loss formulation                                                                                                                                                                                                                           | Problem Domain                         |
|---------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------|
| [2]           | Loss function with two components. One for multimodal fusion and other for news similarity. $\alpha, \beta$ is the weights assigned o each component. | $L = \alpha L_p + \beta L_s$<br>Where,<br>$L_p$ and $L_s$ are based on cross entropy loss.                                                                                                                                                 | Fake News Detection.                   |
| [4]           | Weighted sum of two loss function namely cross entropy loss(CE-Loss) and mean squared error(MSE).                                                     | $L = L_{CE} + w(t)L_{MSE}$<br>Where,<br>$w(t)$ is unsupervised weight.                                                                                                                                                                     | Fake News Detection.                   |
| [9]           | Loss functions for ensemble models with two components where components focus on model accuracy and diversity.                                        | $L(y^{\wedge}, y) = \mu L_{class}(y^{\wedge}, y) + (1 - \mu)L_{div}(y^{\wedge})$<br>Where,<br>$L_{class}(y^{\wedge}, y)$ is mean of CE and Focal Loss.<br>$L_{div}(y^{\wedge})$ is the term responsible for diversity among base learners. | Fake News Detection.                   |
| [11]          | Parameter-free loss which uses average of sample probability of each class in cross entropy loss.                                                     | $Par F = -\frac{1}{C} \sum_{i=1}^C \log(q_i)$<br>and<br>$q_i = \frac{1}{S_i} \sum_{j=1}^{S_i} p_j$                                                                                                                                         | Class imbalance in Image segmentation. |
| [12]          | Introduces weights on cross entropy loss. Weights are cost of missing a positive or negative sample.                                                  | $L_{RWCE} = -\frac{1}{M} \sum_{i=1}^M w_{cfn}(y_i \log y_i^p) + w_{cfp}(1 - y_i) \log(1 - y_i^p)$                                                                                                                                          | Class imbalance problem.               |

Source: Authors, (2026).

### III. PROPOSED METHODOLOGY:

This section first discussed the two approaches through which the multimodal deep learning model for fake news detection is designed. Further the proposed three loss functions are presented with formulas and mathematical modeling.

#### III.1 HIERARCHICAL DEEP LEARNING MODEL

This model for fake news detection employs two approaches are early fusion and ensemble learning. In early fusion, text, image and social context features are extracted and combined into a unified multimodal feature representation which is then down sampled for classification. The attention mechanism is used to capture cross modal features. In the ensemble approach, each modality is processed by independent models and their predictions are combined using a weighted average. The custom loss functions AHL, FNL and SPL are integrated into these models to optimize the learning process by penalizing misclassified samples and ensuring balanced precision and recall.

##### III.1.1 Learning Through Multimodal Shared Feature Representation

In this approach, relevant features are extracted from different modalities. Early fusion is done to generate a shared multimodal feature representation. This feature vector is further down sampled for final classification. Different techniques and approaches are used to generate shared feature representation [12], [13], most popular being the attention mechanism. The attention mechanism has the ability to recognize the intramodality features which is critical in accurate multimodal fake news detection. Such learned shared feature representation will be biased towards majority class if trained on imbalanced datasets. Hence, we design custom loss functions for such model. Figure 1 shows the Hierarchical deep learning architecture with early fusion and proposed loss. At first the modality specific features are extracted from the multimodal data, the extracted features  $E_t$ ,  $E_v$  and  $E_s$  are fused using early fusion to get one feature vector, this feature vector classification is optimized using optimizer and proposed loss functions.

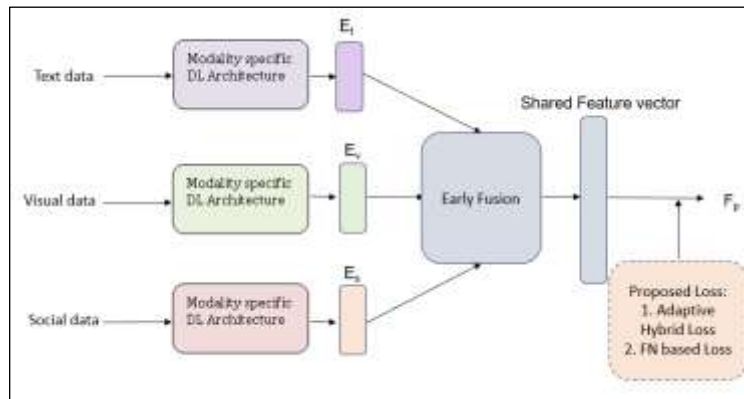


Figure 1: Architecture of Hierarchical DL model showing early fusion and feature extraction from text, images and social context data.

Source: Authors, (2026).

### III.1.2 Learning Through Multimodal Ensemble

Ensemble learning is a powerful approach for designing multimodal fake news detection systems. In this approach, feature extractors are developed for each modality (text, image, and social context), and the predictions from these extractors are combined to make the final prediction. This method create simplified models but fail to capture the intermodality features result is less accurate models. The Figure 2 shows the architecture of ensembled based system for Fake news Detection. In this work, we proposed SPL which forces the ensemble model to make closer and similar predictions resulting in improved accuracy.

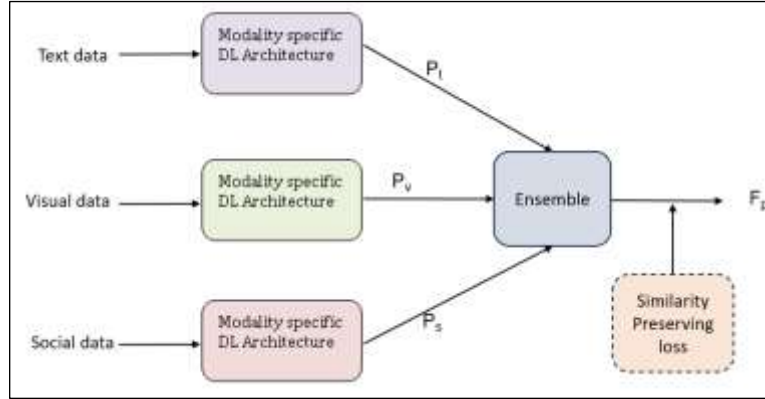


Figure 2: Ensemble-based multimodal model with SPL.

Source: Authors, (2026).

### III.1.3 Proposed Adaptive Hybrid Loss Function

Since there are more misclassified samples in the first training phase, BCE and FL are given almost identical weights. However, as the training goes on and predictions become more accurate, there are less misclassified samples, therefore FL's weight declines. Cross-entropy binary loss is effective for binary classification tasks and helps the model distinguish between fake and real news. In cases of highly imbalanced and real-world datasets, where fake news instances are much rarer than real news and vice versa, this loss function alone may not suffice. Focal loss on the other hand addresses this issue by down-weighting the loss contribution of well-classified examples, enabling the model to focus more on hard-to-classify examples, but focal loss also has limitations when it comes to dynamic data distribution in training. By combining these two loss functions and adding adaptive weights, the AHL function ensures a balanced optimization process, improving the model's ability to accurately classify fake news while mitigating the impact of data imbalance. This approach allows for better handling of challenging examples and enhances the overall performance of the multimodal fake news detection model. The equation of the AHL is given below. Refer the equation (1) for BCE loss.

$$AHL = \sum_{i=1}^B w * L_{BCE} + (1 - w) * L_{BFL} \quad (3)$$

$$\text{Where } w = \frac{L_{BCE}}{L_{BCE} + L_{BFL}} \quad (4)$$

$$L_{BFL} = -\frac{1}{N} \sum_{i=1}^N y_i (1 - \hat{y}_i)^\gamma \log \hat{y}_i + (1 - y_i) \hat{y}_i^\gamma \log(1 - \hat{y}_i) \quad (5)$$

N is the number of samples in a batch "B",  $\hat{y}_i$  is the predicted probability and  $y_i$  is the class label. In the study the weights are set manually as well learned adaptively batch wise during the training phase. In adaptive weight calculation, the weight w is adjusted based on the proportion of the total loss that is due to BCE loss. It essentially normalizes the BCE loss with respect to the combined loss, thereby dynamically adjusting the weight based on the current performance of the model. Batch size plays a crucial role while implementing the AHL. If a batch under execution has balanced samples for both the classes, the weight 'w' will be high giving more importance to BCE loss and (1-w) weight to the focal loss and vice versa.

### III.1.4 FN Based Loss (FNL)

The above-designed hybrid loss functions are further modified to suit the performance needs of the fake news detection problem. Here the false negatives should be penalized heavily as compared to the false positives. Considering this, rather than applying a full focal loss, we incorporate only a fraction of the focal loss, scaled by the false negative ratio, into the overall loss calculation. The equation for the FN based loss is as follows:

$$FNL = \sum_{i=1}^B L_{BCE} + \mu * L_{BFL} \quad (6)$$

Where the value of  $\mu$  is calculated as follows:

$$\mu = \frac{\text{False Negatives (FN)}}{\text{Total Samples}} \quad (7)$$

$$FN = \sum_{i=1}^N I_1(y = 1, \hat{y} \leq 0.5) \quad (8)$$

In the equation (3)  $\mu$  is the false negative probability,  $I_1$  is the indicator functions which returns 0,1 according to the condition satisfied. The key advantage of this arrangement lies in its targeted penalization approach. By scaling the focal loss component according to the false negative ratio, we ensure that the model pays appropriate attention to false negatives which in turn contributed in increasing the overall recall of the system.

Algorithmic pseudocode for AHL and FNL.

```

Algorithm 1: AHL and FNL
Input: Y_true, # The true labels of the batch
      Y_prediction #The predicted labels of the batch,
Output: Classification of shared feature vector to real or fake.
Procedure:
1.   Initialize constants: epsilon  $\epsilon$  # A small value to prevent divide by zero
      Gamma  $\gamma$  #
2.   Compute BCE Loss
2.1  $loss_{pos} = -Y_{true} * \log(Y_{prediction})$  #BCE loss for positive samples
2.2  $loss_{neg} = -(1 - Y_{true}) * \log(1 - Y_{prediction})$  #BCE loss for negative sample
2.3  $L_{BCE} = loss_{pos} + loss_{neg}$ 
    2.4 Compute mean LBCE
3.   Compute Focal Cross-Entropy (FCE) Loss
3.1  $p_t = (Y_{true} * Y_{prediction}) + (1 - Y_{true}) * (1 - Y_{prediction})$ 
3.2  $L_{BFL} = -(1 - p_t)^\gamma * \log(p_t)$  # FL loss for a sample
3.3 Compute mean LBFL
4.   Calculate the final loss
4.1 For AHL: Apply the formula of AHL
4.2 For FNL: Apply formula of FNL.
return (final_loss)

```

### III.2 SIMILARITY PRESERVING LOSS (SPL):

The proposed novel loss function incorporates a similarity-preserving mechanism to BCE loss and is tailored for ensemble learning architectures in fake news detection. This loss function seeks to improve the performance of the ensemble by incorporating a mechanism that evaluates the similarity between the predictions of the independent feature extractors. These metrics quantify how closely the feature extractor's outputs align with each other. Based on the calculated differences, the modulating term of the focal loss is modified. The equation of proposed loss function is as follows.

$$SPL = L_{BCE} + \alpha_t (Sim(T_t, I_t, S_t))^\gamma \log(p_t) \quad (9)$$

Where  $p_t = p_t$  if class label is 1 and  $p_t = (1 - p_t)$  if class label is 0.

$$Sim = \frac{2}{m(m-1)} \sum_{i=1}^m \sum_{j=i+1}^m similarity(i, j) \quad (10)$$

And  $m$  is the number of feature extractors in the ensemble,  $\gamma$  is the modulating term and relative absolute distance is used as a similarity measure. Ensembles with similar predictions incur fewer penalties, promoting consensus among the feature extractors. Conversely, when there is significant divergence in predictions, the penalty increases encouraging the feature extractors to update the weights and get detailed insights from the model.

Algorithmic pseudocode for SPL.

```

Algorithm 2: SPL
Input: Y_true, # The true labels of the batch
      Y_prediction #The predicted labels of the batch,
      T_t #text feature extractor output
      I_t #image feature extractor output
      S_t #Social Context feature extractor output
Output: real or fake.
Procedure:
1.   Initialize constants: epsilon  $\epsilon$  # A small value to prevent divide by zero
      Gamma  $\gamma$ 
      Alpha  $\alpha$ 
2.   Compute BCE Loss
2.1  $loss_{pos} = -Y_{true} * \log(Y_{prediction})$  #BCE loss for positive samples
2.2  $loss_{neg} = -(1 - Y_{true}) * \log(1 - Y_{prediction})$  #BCE loss for negative sample
2.3  $L_{BCE} = loss_{pos} + loss_{neg}$ 
    2.4 Compute mean LBCE
3.   Compute the similarity term using equation (10)
4.   Calculate the final loss by applying equation (9)
return (final_loss)

```

### III.3 MATHEMATICAL MODELLING OF CUSTOM LOSS FUNCTIONS

The AHL combines BCE and FL dynamically adjusting the weight between them based on batch accuracy. For instance, in an imbalanced batch where most samples are misclassified, the weight towards FL which prioritizing hard to classify examples. The FN based penalizes false negatives by scaling the focal loss based on the proportion of false negatives in the batch ensuring that fake news is detected more effectively. The SPL encourages consensus among ensemble models by penalizing discrepancies in predictions across modalities. Proposed loss function defined in equation (3) depends upon the BCE loss and focal loss calculated during the training. The proportion of these losses to be considered during training is governed by the weight 'w' which in turn depends upon the batch size chosen for training the deep learning model. Table 2 provide the weights dynamics for a batch size of 8. To illustrate the effectiveness of the loss function, we analysed three scenarios using a batch size of 8. The scenarios are as follows:

- **Worst Case:** Only 10% of the samples (1 out of 8) are correctly classified.
- **Average Case:** 60% of the samples (5 out of 8) are correctly classified.
- **Best Case:** 90% of the samples (7 out of 8) are correctly classified.

Table 2: Weight dynamics of AHL across different sample classification scenarios.

| Sample size | Scenario                                          | BCE    | FL     | Weight 'w' | BCE contribution | FL contribution | loss   |
|-------------|---------------------------------------------------|--------|--------|------------|------------------|-----------------|--------|
| 8           | <b>Worst (10% samples correctly classified)</b>   | 0.4865 | 0.2685 | 0.6443     | 0.3134           | 0.0955          | 0.4089 |
|             | <b>Average (60% samples correctly classified)</b> | 0.3184 | 0.1569 | 0.6698     | 0.2133           | 0.0518          | 0.2651 |
|             | <b>Best (90% samples correctly classified)</b>    | 0.1863 | 0.0470 | 0.7983     | 0.1487           | 0.0094          | 0.1582 |

Source: Authors, (2026).

In the initial phrase of training, the weight assigned to BCE and FL are almost equal since in initial phrase there are more misclassified samples, as the training progresses the weight of FL decreases as predictions are becoming more accurate resulting in less misclassification. Equation (6) gives the FN-based loss function. For each scenario, we consider three different weights  $\mu = 0, 0.5, 1$  and calculate the corresponding values of BCE Loss, Focal Loss, and the total hybrid loss. The table 3 below summarizes the results:

Table 3: Weight dynamics of FNL.

| Sample size | Scenario                                          | Case                             | BCE    | FL     | False Negative Probability ( $\mu$ ) | BCE contribution | FL contribution | loss   |
|-------------|---------------------------------------------------|----------------------------------|--------|--------|--------------------------------------|------------------|-----------------|--------|
| 8           | <b>Worst (10% samples correctly classified)</b>   | FN =0 in given sample size       | 0.4865 | 0.2685 | 0                                    | 0.4865           | 0               | 0.4865 |
|             |                                                   | FN=x, where x is total samples.  |        |        | 1                                    | 0.4865           | 0.2685          | 0.7556 |
|             |                                                   | FN=y, total samples=x, $y < x$ . |        |        | 0.5                                  | 0.4865           | 0.1342          | 0.6207 |
| 8           | <b>Average (60% samples correctly classified)</b> | FN =0 in given sample size, FP=x | 0.2991 | 0.1478 | 0                                    | 0.2991           | 0               | 0.2991 |
|             |                                                   | FN=x, where x is total samples.  |        |        | 1                                    | 0.2991           | 0.1478          | 0.4469 |
|             |                                                   | FN=y, total samples=x, $y < x$ . |        |        | 0.5                                  | 0.2991           | 0.0739          | 0.3734 |
| 8           | <b>Best (90% samples correctly classified)</b>    | FN =0 in given sample size, FP=x | 0.1863 | 0.0470 | 0                                    | 0.1863           | 0               | 0.1863 |
|             |                                                   | FN=x, where x is total samples.  |        |        | 1                                    | 0.1863           | 0.0470          | 0.2333 |
|             |                                                   | FN=y, total samples=x, $y < x$ . |        |        | 0.5                                  | 0.1863           | 0.0235          | 0.2098 |

Source: Authors, (2026).

A value of  $\mu=1$  indicates that the current batch contains all false negatives, resulting in a high total loss due to the severe penalty for misclassifying positive samples. Conversely,  $\mu=0$  indicates that the batch contains no false negatives, leading to a lower total loss as the primary focus is on reducing false negatives. When the batch has half number of false negatives,  $\mu=0.5$ . In this balanced scenario, the loss incurred reflects a combination of both BCE and Focal Loss, providing a middle-ground penalty that encourages the model to address both types of errors equally. This adaptive approach ensures that the model remains sensitive to the distribution of False Negatives in each batch, allowing for more effective and targeted learning.

The SPL is shown in equation (9) evaluates how dissimilar a prediction of a particular modality feature extractor is from the other feature extractors and adjusts the weights accordingly. By doing so, it promotes consistency among the multimodal feature extractors, leveraging the interrelated nature of multimodal data.

Table 4: Mathematical modelling of SPL.

| Scenario   | Text | Image | Social Context | Average Distance | Ensemble Prediction (Average) | BCE    | FL     |
|------------|------|-------|----------------|------------------|-------------------------------|--------|--------|
| Dissimilar | 0    | 1     | 1              | 0.66             | 0.66                          | 0.1760 | 0.0782 |
|            | 1    | 0     | 0              | 0.66             | 0.33                          | 0.4771 | 0.2120 |
|            | 0.2  | 0.8   | 0.46           | 0.4              | 0.48                          | 0.3127 | 0.0500 |
| Similar    | 0.9  | 0.9   | 0.9            | 0                | 0.9                           | 0.0457 | 0      |
|            | 0.6  | 0.5   | 0.56           | 0.06             | 0.55                          | 0.2570 | 0.0011 |
|            | 0.8  | 0.6   | 0.7            | 0.13             | 0.7                           | 0.1549 | 0.0027 |

Source: Authors, (2026).

The table 4 presents six scenarios to illustrate the effectiveness of the proposed SPL function for class '1' i.e 'Fake' class. Three scenarios involve feature extractors with dissimilar predictions, and three involve feature extractors with similar predictions. In scenarios where the feature extractors' predictions are highly dissimilar and ensemble final prediction is also incorrect, the Focal Loss (FL) contribution is significantly higher in SPL. In scenarios of similar predictions, where the feature extractor's predictions are similar, and ensemble prediction is correct, the Focal Loss contribution in SPL is minimal. This encourages the feature extractors to produce more consistent and correlated predictions.

#### IV. EXPERIMENTS

In this work, the proposed three loss functions are compared against the popular BCE loss, and focal loss, which are commonly used in the literature. The details of hyper parameters used for training the models with proposed loss functions is presented in table 5. The comparison of the proposed losses with the above-mentioned losses is done based on the following aspects: 1) Stability and consistency while training the model with different losses.2) Evaluation of losses against performance metrics: Precision, Recall, F1-Score, Accuracy and AUC-ROC.3) Generalizing ability of the trained model.

Table 5: Hyper parameters used for training deep learning model.

| Hyper parameters | Values                               |
|------------------|--------------------------------------|
| Number of Epochs | 20                                   |
| Train test split | 80:20                                |
| Loss functions   | BCE, FL and proposed loss functions. |
| Optimizer        | Adam                                 |

Source: Authors, (2026).

#### IV.1 DATASETS

The designed loss functions are tested in context of fake news detection. Three real world multimodal dataset are used and experimented in the study. The datasets are as follows:

- 1.Fake News Net [23]: It is a multi-dimensional real-world dataset of news collected from Gossip Cop and Politick. Along with the news contents it provides visual and social context information about the news post.
- 2.Fake edit [24]: It is a multimodal dataset widely used in fake news detection. It provides text, image and limited social context data about news post.
- 3.Twitter Media Eval [25]: The data released for Mediaeval challenge for recognizing misleading content and post propagation on social media.

The distribution of samples in this dataset is shown in table 6:

Table 6: Real and fake sample distribution for the three real world datasets.

| Dataset            | Fake Samples | Real Sample | Total |
|--------------------|--------------|-------------|-------|
| Fake edit          | 1552         | 1094        | 2646  |
| Fake News Net      | 1742         | 1071        | 2813  |
| Twitter Media Eval | 3681         | 1991        | 5672  |

Source: Authors, (2026).

#### IV.2 EXPERIMENTAL SETUP

Google Colab Pro with a hardware accelerator T4 GPU and high RAM facility was used to train the models. The model and loss functions implementation are done using Python, with Tensor Flow and Keras libraries.

### IV.3 RESULT AND ANALYSIS

#### IV.3.1 Training Stability and Convergence using Different Loss Functions

Here we evaluate the training and validation accuracy and loss plots across three different loss functions: FL, BCE Loss and proposed AHL, FNL and SPL. Evaluation is done for stable training and convergence. Stability during the training process is demonstrated by smooth training and validation curves in accuracy and loss plots. Stability can be seen in BCE and proposed loss functions as there are minimum fluctuations in the curves as training progresses. In case of focal loss sudden and abrupt fluctuations can be seen. Convergence is seen when the training and validation curves meet and remain close for further epochs. Convergence is seen in focal loss and proposed loss functions and not in case of BCE loss as gap between training and validation curves is visible. Figure 3,4 provides the training and validation accuracy and loss plots for models trained using focal loss, BCE, AHL, FNL and SPL.

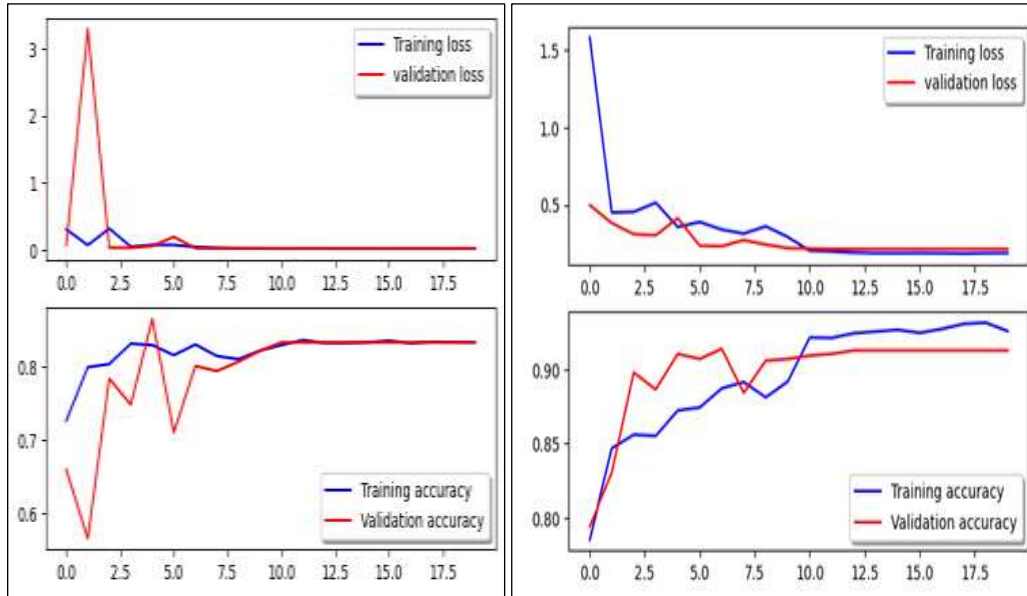


Figure 3: Training and validation loss and accuracy plots for (from left) Focal loss and BCE loss for Fake News Net Dataset. Source: Authors, (2026).

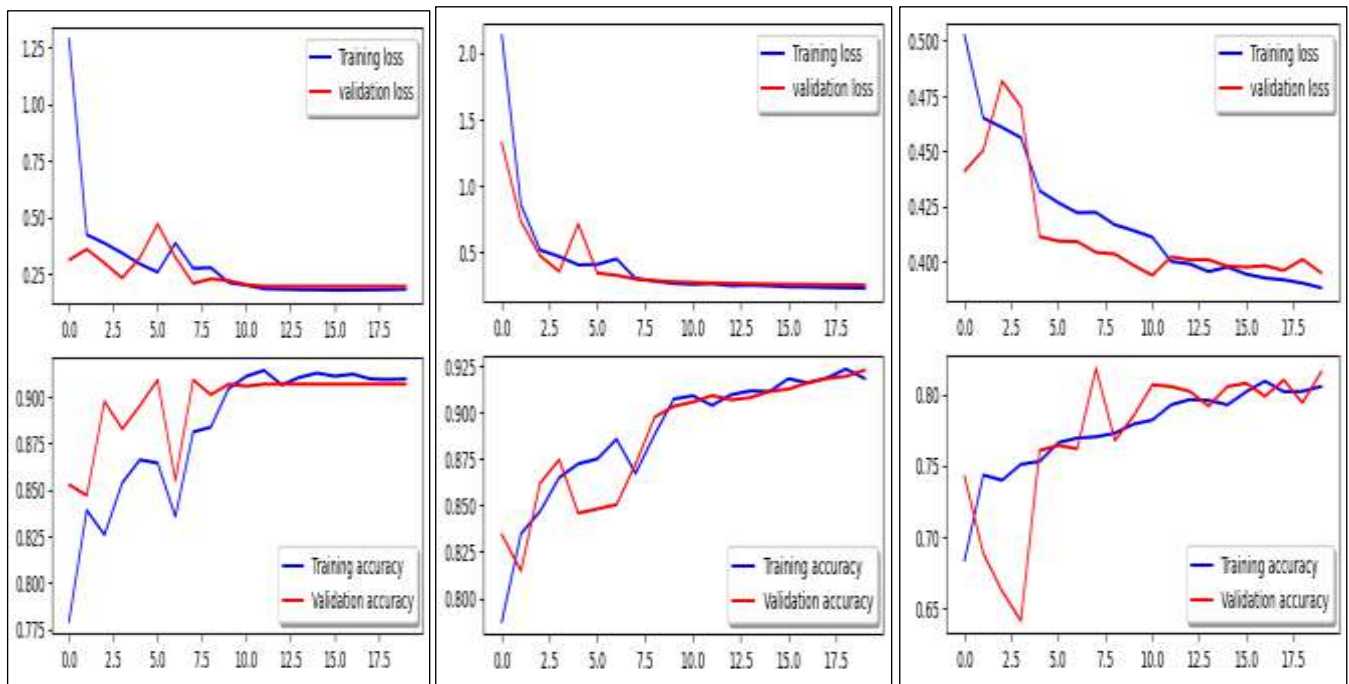


Figure 4: Training and validation accuracy and loss plots for the proposed loss function for Fake News Net Dataset. In the left is AHL, centre is FN based AHL and on right is the SPL. Source: Authors, (2026).

Thus, proposed loss functions demonstrate stability and convergence during training. This indicates that the training process is well-behaved and not prone to sudden changes and model's performance improves steadily over epochs.

### IV.3.2 Evaluation of Losses Function Against Performance Metrics:

In this section, we analyse the performance of early fusion and decision level fusion models with existing loss functions and the proposed loss functions on the Fake News Net dataset. The results are presented in a tabular format, including accuracy, precision, recall, F1 score, false positive rate, false negative rate, and ROC-AUC. Table 7 provides the performance of early fusion model, when trained using proposed loss functions and loss functions available in literature. We first applied the existing loss functions from the literature: BCE, and FL on the Fake News Net dataset. The BCE loss does not achieve good balance between the recall and precision resulting in comparative low F1 score and ROC-AUC. Focal loss shows a significant difference between precision (64.63%) and recall (92.86%) resulting in low F1 score of 76.31%. We then applied the proposed AHL and FNL on the Fake News Net dataset. Model trained using AHL achieves a balance between precision and recall resulting in high F1 score (92.70%). The FNL is successful in reducing the false negatives and provides a high recall of the model.

Table 7: Performance Evaluation of Early fusion model trained with different loss functions.

| Loss               | Accuracy     | Precision    | Recall       | F1 Score     | False Positive Rate | False Negative rate | ROC-AUC      |
|--------------------|--------------|--------------|--------------|--------------|---------------------|---------------------|--------------|
| Cross entropy loss | 91.25        | 89.59        | 92.21        | 90.88        | 9.60                | 7.78                | 90.89        |
| Focal loss         | 80.34        | 64.63        | 92.86        | 76.31        | 35.31               | 6.54                | 81.52        |
| AHL                | <b>92.75</b> | <b>92.02</b> | <b>92.70</b> | <b>92.36</b> | <b>7.20</b>         | <b>7.29</b>         | <b>92.45</b> |
| FN based AHL       | <b>91.82</b> | <b>89.90</b> | <b>93.18</b> | <b>91.51</b> | <b>9.38</b>         | <b>6.81</b>         | <b>91.20</b> |

Source: Authors, (2026).

The confusion matrix for the BCE and proposed loss function is shown in table 8. The confusion matrix of AHL demonstrates that there is balanced and reduced false positives and false negatives in the model. Confusion matrix of FNL demonstrates reduction in false negatives i.e instances where fake news is classified as real and increased in True positives thus achieving target specific learning.

Table 8: Confusion matrix values for the models with BCE loss and proposed AHL and FNL.

| Loss Function       | True Positive (TP)<br>(Fake news classified as fake) | True Negative (TN)<br>(Real news classified as real) | False Negative (FN)<br>(Fake news classified as Real) | False Positive (FP)<br>(Real news classified as Fake) |
|---------------------|------------------------------------------------------|------------------------------------------------------|-------------------------------------------------------|-------------------------------------------------------|
| Model with BCE loss | 379                                                  | 414                                                  | 32                                                    | 44                                                    |
| Model with AHL      | <b>381</b>                                           | <b>425</b>                                           | <b>30</b>                                             | <b>33</b>                                             |
| Model with FNL      | <b>383</b>                                           | <b>415</b>                                           | <b>28</b>                                             | <b>43</b>                                             |

Source: Authors, (2026).

The proposed loss was further experimented with by manually setting the weights. Table 9 shows the results of manual and adaptive weights. The proposed loss with adaptive weights outperforms the manual version of the proposed loss function. Further Figure 5 provides the loss plots of adaptive and manual version of hybrid loss. It can be seen that AHL and FNL demonstrates smooth and decreasing curve.

Table 9: Performance Evaluation of Early fusion model trained with proposed loss functions using manual weights.

| Hybrid Loss(BCE+FL)             | Accuracy     | Precision    | Recall       | F1 score     | ROC-AUC      |
|---------------------------------|--------------|--------------|--------------|--------------|--------------|
| Manual weights (W1=W2=0.5)      | 89.85        | 90.58        | 91.67        | 91.12        | 90.02        |
| Manual weights (W1=0.8,W2=0.2)  | 89.10        | 85.53        | 92.70        | 88.81        | 88.89        |
| Manual weights (W1=0.7, W2=0.3) | 91.25        | 90.95        | 90.51        | 90.73        | 90.82        |
| AHL                             | <b>92.75</b> | <b>92.02</b> | <b>92.70</b> | <b>92.36</b> | <b>92.45</b> |
| FN based AHL                    | <b>91.82</b> | <b>89.90</b> | <b>93.18</b> | <b>91.51</b> | <b>91.20</b> |

Source: Authors, (2026).

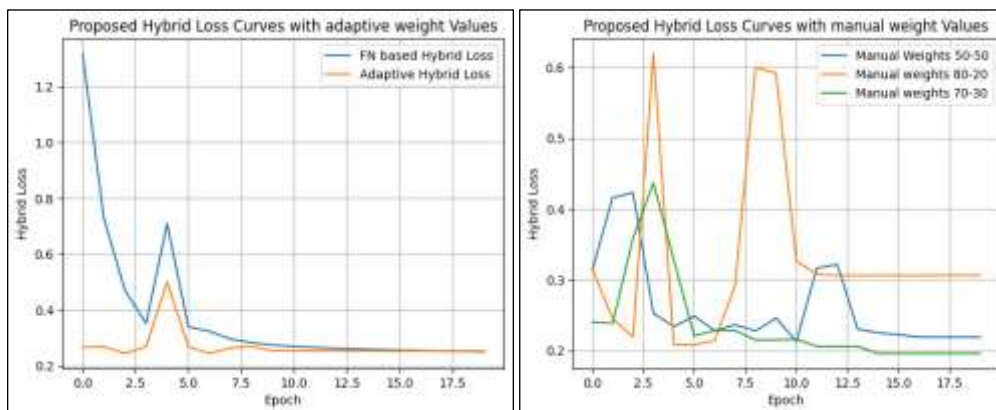


Figure 5: Loss plots of AHL, FNL and its manual versions.

Source: Authors, (2026).

Table 10: Performance Evaluation of Decision level (ensemble) fusion model trained with different loss functions.

| Loss                      | Accuracy     | Precision    | Recall       | F1 Score     | False Positive Rate | False Negative rate | ROC-AUC      |
|---------------------------|--------------|--------------|--------------|--------------|---------------------|---------------------|--------------|
| <b>Cross entropy loss</b> | 88.49        | 92.83        | 81.99        | 87.08        | 18.00               | 5.67                | 88.15        |
| Focal loss                | 80.34        | 64.63        | 92.86        | 76.31        | 35.31               | 6.54                | 81.52        |
| Proposed SPL              | <b>91.13</b> | <b>90.93</b> | <b>90.26</b> | <b>90.59</b> | <b>8.07</b>         | <b>9.73</b>         | <b>90.69</b> |

Source: Authors, (2026).

Similarly, we applied BCE, FL and SPL to the ensemble deep learning model trained on Fake news net dataset. Table 10 provides the performance evaluation of this ensemble model and table 11 provides the confusion matrix for the same. Proposed SPL outperforms the BCE and FL loss which are commonly used in literature.

Table 11: Confusion matrix values for the models with BCE loss and proposed SPL.

| Loss Function       | True Positive (TP)<br>(Fake news classified as fake) | True Negative (TN)<br>(Real news classified as real) | False Negative (FN)<br>(Fake news classified as Real) | False Positive (FP)<br>(Real news classified as Fake) |
|---------------------|------------------------------------------------------|------------------------------------------------------|-------------------------------------------------------|-------------------------------------------------------|
| Model with BCE loss | 337                                                  | 432                                                  | 74                                                    | 26                                                    |
| Model with SPL      | <b>371</b>                                           | <b>421</b>                                           | <b>40</b>                                             | <b>37</b>                                             |

Source: Authors, (2026).

The figure 6 comparative bar chart representation of all the loss functions studies in the work against the F1 score and recall. Thus, model with FNL provides the highest recall of followed by AHL and BCE. The AHL provides the highest F1 score followed by FNL and BCE, SPL loss.

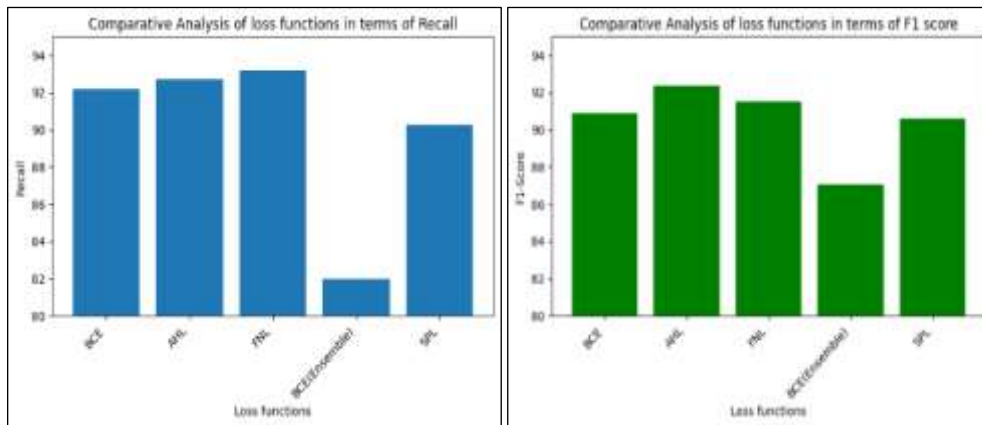


Figure 6: Comparative chart for F1 score and recall.

Source: Authors, (2026).

#### IV.3.3 The Generalizing Ability of the Model with Loss Functions

To ensure that the proposed loss functions generalize across different datasets, this study evaluated them on the FakeNewsNet, FakeEdit and Twitter MediaEval datasets. The AHL consistently balanced precision and recall while the FN based loss significantly improved recall by penalizing false negatives. Generalization tests revealed that the models trained using these loss functions maintained robust performance across all datasets demonstrating their adaptability top different data sources and real world scenarios. The results of testing the models on FakeEdit and Twitter MediaEval datasets are presented in the tables 12.

Table 12: Performance of the proposed losses on Fake edit and twitter media eval datasets.

| Loss               | Dataset                       | Accuracy     | Precision    | Recall       | F1 Score     | ROC-AUC      |
|--------------------|-------------------------------|--------------|--------------|--------------|--------------|--------------|
| FakeEdit           | BCE                           | 71.24        | 70.86        | 62.93        | 66.66        | 70.11        |
|                    | <b>Proposed AHL</b>           | <b>72.34</b> | <b>71.67</b> | <b>70.81</b> | <b>71.23</b> | <b>71.21</b> |
|                    | <b>Proposed FN based loss</b> | <b>71.45</b> | <b>69.52</b> | <b>81.43</b> | <b>75.00</b> | <b>73.81</b> |
|                    | SPL                           | 60.12        | 53.58        | 94.95        | 68.51        | 60.11        |
| Twitter Media Eval | BCE                           | 85.64        | 84.41        | 78.42        | 82.48        | 84.44        |
|                    | <b>Proposed AHL</b>           | <b>88.12</b> | <b>87.47</b> | <b>87.12</b> | <b>87.29</b> | <b>87.92</b> |
|                    | <b>Proposed FN based loss</b> | <b>88.54</b> | 78.90        | <b>94.42</b> | 85.96        | <b>89.74</b> |
|                    | SPL                           | 86.89        | 82.95        | 81.45        | 82.19        | 85.77        |

Source: Authors, (2026).

The experimental results on the FakeEdit and Twitter MediaEval datasets demonstrate that the proposed loss functions not only perform well on the initial FakeNewsNet dataset but also generalize effectively to other similar datasets. The AHL and FNL functions consistently achieve high recall and low false negative rates, while maintaining a balance between other performance metrics. This indicates their robustness and effectiveness in addressing the challenges of fake news detection across diverse social media platforms.

## V. CONCLUSION

In the realm of deep learning-based fake news detection systems, the commonly used cross-entropy loss function often falls short when models are trained on real-world imbalanced datasets. To address this challenge, our work proposes three novel loss functions: AHL, FNL, and SPL. The FN-based Loss specifically targets improving the recall of the model by focusing on reducing false negatives, which is crucial for fake news detection. The AHL is designed for scenarios where both precision and recall are equally important, providing a balanced performance by adjusting weights to balance these metrics. Additionally, we introduced the SPL for ensemble-based fake news detection systems. These systems typically utilize a simplified architecture but finds it difficult to achieve optimal results due to the independent training of base models. Our proposed loss function encourages similar predictions among base learners and penalizes discrepancies, thereby improving overall accuracy and consistency. The AHL demonstrated balanced performance on imbalanced datasets and was further tested for generalization on two other real-world datasets: FakeEdit and Twitter MediaEval. It achieved an F1 score of 91.83% on FakeNewsNet, 71.23% on FakeEdit, and 87.29% on Twitter MediaEval, outperforming the standard BCE loss. The FN-based Loss successfully enhanced the recall of the model, increasing true positives and reducing false negatives. It achieved a recall of 93.18% on FakeNewsNet, 81.43% on FakeEdit, and 94.42% on Twitter MediaEval, all of which are higher than those obtained using BCE loss. In the future, we aim to test the proposed loss functions on other real-world imbalanced datasets beyond the domain of fake news detection to further validate their effectiveness and generalizability.

## VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** Deepti Deepak Nikumbh, Anuradha Thakare.

**Methodology:** Deepti Deepak Nikumbh, Anuradha Thakare.

**Investigation:** Deepti Deepak Nikumbh, Anuradha Thakare.

**Discussion of results:** Deepti Deepak Nikumbh, Anuradha Thakare.

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**Writing – Review and Editing:** Deepti Deepak Nikumbh, Anuradha Thakare.

**Resources:** Deepti Deepak Nikumbh.

**Supervision:** Deepti Deepak Nikumbh, Anuradha Thakare.

**Approval of the final text:** Deepti Deepak Nikumbh, Anuradha Thakare.

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