# Saliency-Aware Interpolative Augmentation for Multimodal Financial Prediction

Samyak Jain<sup>1\*</sup>, Parth Chhabra<sup>1\*</sup>, Atula Neerkaje<sup>2\*</sup>, Puneet Mathur<sup>3</sup>, Ramit Sawhney<sup>4,5</sup>, Shivam Agarwal<sup>6</sup>, Preslav Nakov<sup>5</sup>, Sudheer Chava<sup>4</sup>, Dinesh Manocha<sup>3</sup>

IIIT Delhi-India<sup>1</sup>, UT Austin-United States<sup>2</sup>, University of Maryland-United States<sup>3</sup>, Georgia Institute of Technology-United States<sup>4</sup>, Mohamed bin Zayed University of Artificial Intelligence-UAE<sup>5</sup>, University of Illinois Urbana-Champaign-United States<sup>6</sup> {parth19069, samyak19098}@iiitd.ac.in, atulaj@utexas.edu, {puneetm, dmanocha}@umd.edu, rsawhney31@gatech.edu / {ramit.sawhney, preslav.nakov}@mbzuai.ac.ae, shivamag99@gmail.com, sudheer.chava@scheller.gatech.edu

#### Abstract

Predicting price variations of financial instruments for risk modeling and stock trading is challenging due to the stochastic nature of the stock market. While recent advancements in the Financial AI realm have expanded the scope of data and methods they use, such as textual and audio cues from financial earnings calls, limitations exist. Most datasets are small, and show domain distribution shifts due to the nature of their source, suggesting the exploration for data augmentation for robust augmentation strategies such as Mixup. To tackle such challenges in the financial domain, we propose SH-Mix: Saliency-guided Hierarchical Mixup augmentation technique for multimodal financial prediction tasks. SH-Mix combines multi-level embedding mixup strategies based on the contribution of each modality and context subsequences. Through extensive quantitative and qualitative experiments on financial earnings and conference call datasets consisting of text and speech, we show that SH-Mix outperforms state-of-the-art methods by 3-7%. Additionally, we show that SH-Mix is generalizable across different modalities and models.

Keywords: Multimedia Document Processing, Social Media Processing, Tools, Systems, Applications

#### 1. Introduction

Financial risk modelling is of great interest to capital market participants for making sound investment decisions comprising tasks like price forecasting and movement/volatility prediction which are essential to designing profitable trading strategies. Nevertheless, forecasting trends in these valuations is a complex task due to the inherent kinetic characteristics and volatility of the stock market.

Recent works establish the effectiveness of incorporating multimodal data from diverse sources like financial news (Hu et al., 2018), social media (Tabari et al., 2018) and financial documents (Mathur et al., 2022a) over conventional statistical methods using historical price data (Zheng et al., 2019; Ariyo et al., 2014a; Wu et al., 2022). Financial conference calls are one such rich information source consisting of textual, auditory and visual cues (Price et al., 2012; Brockman et al., 2017), and exhibit correlation with the involved firms' stock prices (Irani, 2004; Bowen et al., 2000). Examples include earnings calls, mergers and acquisitions calls, and monetary policy briefings which typi-



Figure 1: Example from a financial earnings call showing that not every part of the input has same relevance for price movement forecasting task. More salient spans are colored darker. There are evident variations in the degree of saliency observed within distinct hierarchical levels, specifically at the modality-level and the fused-level.

cally feature spoken content from senior executives and offer valuable insights into a company's performance. Including vocal cues along with explicit textual information enriches the learned representations with information about tonality, intonations, and pitch, which serve as indicators of underlying emotions and sentiment of the speaker, thereby

<sup>\*</sup>Equal Contribution

also making them contextually enhanced. Recent studies use multimodal fusion-based mechanisms to harness the contextual information for individual modalities within these calls, while simultaneously incorporating inter-modal relationships (Qin and Yang, 2019; Sawhney et al., 2021; Li et al., 2020; Mathur et al., 2022b). However, there is a scarcity of these real-world multimodal financial datasets, like financial earnings calls which can be as low as four calls per year (Chen et al., 2018). Additional challenges arise in the form of source variations and the need for meticulous annotation. To mitigate this scarcity, we explore Mixup (Zhang et al., 2018) as a data augmentation technique due to its established effectiveness in improving generalization ability in limited data domains (both unimodal and multimodal) (Chidambaram et al., 2022; Zhao et al., 2023; Lin and Hu, 2023; Liu et al., 2023).

Financial data, including conference and policy calls, comprises extensive long-form content, featuring extended audio-visual recordings (Behre et al., 2022), lengthy textual transcripts, typically containing over 5,000 words of text (Koval et al., 2023). Such large data streams contain certain salient segments that have the majority of informational essence (Wilmot and Keller, 2021). Saliencyaware Mixup techniques exploit this saliency information to mix only the most relevant parts of the input reducing noise by considering the discriminative features of the input while also preserving its local structure (Lee et al., 2022; Kim et al., 2020a; Sawhney et al., 2022a). It captures span-level saliencies in unimodal inputs and mixes them by transporting the salient span of one image/audio to another. These approaches utilize saliency from a unimodal perspective and do not consider cross-modal dependencies. As shown in Figure 1, multimodal data streams may contain certain important (salient) aspects to the model's predictions - both locally at the modality level and globally at the fused level, creating a hierarchical structure which is not fully captured by existing Mixup techniques.

Building on these gaps, we propose SH-Mix: Saliency-Aware Hierarchical Multimodal Mixup, a novel hierarchical architecture building on Mixup incorporating saliency information from the underlying data leveraging gradient-based measures. At the local-level, individual modality mixup is conducted based on modality-specific saliency. Subsequently, a second global-level is introduced, wherein these modality-specific representations are fused through an attention-based weighting mechanism, to obtain an abstract multimodal representation. At the global-level, saliency-based mixup is employed on these fused embeddings enabling it to capture the cross-modal correlations and inter-dependencies. Incorporated with a neural multimodal-fusion base, SH-Mix shows significant performance improvement compared to the state-of-the-art approaches. Our contributions are as follows:

- We introduce SH-Mix<sup>1</sup>, a novel data augmentation strategy for multimodal financial data leveraging modality-level and fused-level saliency (§3).
- Through extensive quantitative (§5.1) and exploratory (§5.2, §5.4) experiments on real-world tasks with insufficient training data, such as financial prediction using conference calls, we show that SH-Mix outperforms the existing state of the art by 3-7%.
- Finally, we demonstrate the general applicability of our approach by presenting SH-Mix as a general Mixup framework for multimodal sequence learning through supplementary experiments on tasks from other domains like sarcasm detection and sentiment analysis, and different base models, on data comprising audio, text and visual sequences.(§5.5).

### 2. Related Work

Al in Finance Traditional approaches to financial forecasting employ numerical price-based data to predict future price volatility/movement. These include areas like stock market (Ariyo et al., 2014b; Rundo et al., 2019), cryptocurrencies (K et al., 2022; lgbal et al., 2021) and currency exchange market (Kamruzzaman and Sarker, 2003). These approaches usually employ time-series models like ARIMA (Ariyo et al., 2014b) and GARCH (Bollerslev, 1986). Recently, textual, acoustic and visual signals fetched from social media platforms and web searches have been used for forecasting (Xu and Cohen, 2018; Sawhney et al., 2022b). Such signals are able to capture the underlying investor sentiment associated with financial security beyond just numerical data thus improving the forecasting ability of the model.

**Multimodal Learning in Finance** Recent multimodal learning advances have granted investors access to substantial structured and unstructured multimodal financial data for forecasting (Jiang, 2021). Anecdotal evidence highlights the relevance of non-verbal cues like vocal tone, emotional indicators and language complexity in relation to financial trading (Cao, 2022; Li et al., 2016b; Jiang and Pell, 2017). Studies by Qin and Yang (2019); Sawhney et al. (2020) have exploited multimodal data to predict both price volatility and movement. Mathur et al. (2022b) employed audio, visual, and textual

<sup>&</sup>lt;sup>1</sup>Our code is released at https://github.com/gtfintechlab/shmix

cues from MPC calls to forecast price changes and volatility. The impact of augmentation methods, such as Mixup, during multimodal financial data training remains underexplored.

Mixup (Zhang et al., 2018) is a popular augmentation technique that interpolates two examples along with their corresponding labels. Existing work shows that Mixup performs well on tasks spanning vision, speech, and text (Meng et al., 2021; Chang et al., 2021; Verma et al., 2019; Chhabra et al., 2023; Sawhney and Neerkaje, 2022). Mixup strategies which operate on sequential data such as speech and/or text fail to preserve the locality of inputs while mixing at the input space. Recent work on saliency-based Mixup (Kim et al., 2020b; Ma et al., 2022) look to address this problem by mixing the most important contiguous spans over the raw inputs. Such saliency-based approaches when applied to sequential data, have only been explored in the context of unimodality, such as text (Kong et al., 2022; Yoon et al., 2021) and speech (Sawhney et al., 2022a). Mixup has also lately shown promise in multimodal setups (So et al., 2022; Hao et al., 2023; Meng et al., 2021; Zhou et al., 2023). Zhao et al. (2023) introduce a method which generates new virtual modalities from the mixed token-level representation of raw modalities. However, there is a gap in leveraging the salient components at the modality-level and sequencelevel during Mixup, which is addressed by SH-Mix (§3.4).

### 3. Methodology

#### 3.1. Background

**Mixup** generates virtual samples for training by a convex interpolation of training samples. Given two training samples  $x_i$  and  $x_j$  and their corresponding labels  $y_i$  and  $y_j$ , we generate synthetic sample  $\tilde{x}$  and the corresponding mixed label  $\tilde{y}$  as

$$\tilde{x} = mix(x_i, x_j) = \lambda x_i + (1 - \lambda)x_j \tag{1}$$

$$\tilde{y} = mix(y_i, y_i) = \lambda y_i + (1 - \lambda)y_i$$
<sup>(2)</sup>

 $\lambda \in [0, 1]$  is the mixing ratio (Zhang et al., 2018). In particular, for discrete classification settings,  $y_i$  and  $y_j$  are one-hot encoded labels.

**Saliency** measures the contribution of input / hidden representation features in predicting a specific output class. Gradient-based methods for saliency computation (Simonyan et al., 2014; Li et al., 2016a) are used during training to find features contributing the most towards the prediction. We compute the saliency for an input / hidden representation  $Z = [z_1, z_2, ..., z_n]$  by computing its gradient with respect to the classification loss  $\mathcal{L}$ .

$$\operatorname{sal}(Z; \mathcal{L}) = \frac{\partial \mathcal{L}}{\partial Z} = \left[\frac{\partial \mathcal{L}}{\partial z_1}, \frac{\partial \mathcal{L}}{\partial z_2}, \dots, \frac{\partial \mathcal{L}}{\partial z_n}\right]$$
 (3)

#### 3.2. Problem Formulation

Given an example  $X = [\mathcal{R}^1, \mathcal{R}^2, \dots, \mathcal{R}^N]$  where X is a composite multimodal sequence comprising of N distinct modalities. Each modality  $\mathcal{R}^i$  comprises of a temporal sequence of its raw inputs  $\mathcal{R}^i = [r_1^i, r_2^i, \dots, r_n^i]$  where n is the length of each modality's sequence. All the modalities are temporally aligned.

Following Xu and Cohen (2018), we define *price* movement prediction as a binary classification task which uses the multimodal input X to predict the price movement for the associated firm's stock's closing price over a period of  $\tau$  days following the conference call. We define the movement label  $y_{d-\tau,d}$  as

$$y_{d-\tau,d} = \begin{cases} 1 & p_d > p_{d-\tau} \\ 0 & p_d < p_{d-\tau} \end{cases}$$
(4)

where  $p_d$  is the closing price on the day d.

### 3.3. ADMF: Attention-Driven Multimodal Fusion Architecture

Utilizing low-level modality-specific specialized transformers, such as BERT (Devlin et al., 2019), ViT (Dosovitskiy et al., 2021), and AST (Gong et al., 2021) on raw inputs enables independent processing of each modality at the utterance level, facilitating the capture of modality-specific patterns and yielding contextually rich representations. In line with existing works by Tsai et al. (2019); Mathur et al. (2022b), we first convert the raw modality data into embeddings via low-level transformers  $(\phi_i)$  corresponding to each modality to get  $\mathcal{M}^{i} = \begin{bmatrix} m_{1}^{i}, m_{2}^{i}, \dots, m_{n}^{i} \end{bmatrix}$  where  $m_{i}^{i} = \phi_{i}(r_{i}^{i})$ . We then use an attention-based fusion mechanism that captures the dependency between the modalities. The attention weights  $W'_i$  for a modality are computed via softmax normalization as

$$W_i = \frac{e^{\mathcal{M}^i A^i + b^i}}{\sum\limits_{i=1}^k e^{\mathcal{M}^i A^j + b^j}} \quad \forall i \in [1, 2, \dots, N]$$
(5)

$$W'_{i} = rac{W_{i}}{\sum\limits_{k=1}^{N} W_{k}} \quad \forall i \in [1, 2, \dots, N]$$
 (6)

where  $A^i$  and  $b^i$  represent the attention layer weights learned during the training.

The attention weights are used to weigh the features corresponding to each modality by multiplying these with the respective embeddings to obtain the attended inputs. This adaptive attentionbased weighing mechanism enables the model to selectively focus on the most informative modalities along with temporal dependencies (Hori et al.,



Figure 2: **SH-Mix Overview:** Input text  $\mathcal{T}$  and audio  $\mathcal{A}$  are encoded to yield respective embeddings. Attention weights for each modality are extracted, followed by fusion through weighted summation. The fused representation is fed to transformer block and a dense layer, to obtain the loss. Saliencies are computed for text, audio, and the fused representation via backpropagation, as detailed in section 3.1. These saliencies drive Local-Mix and Global-Mix, resulting in two sets of mixed inputs.

2017; Yan et al., 2020). These are further combined by additive fusion to obtain the intermediate fused multimodal embedding. This is augmented with positional embedding (POS) by addition to obtain the final fused embedding F as follows

$$F = \sum_{j=1}^{N} \mathcal{M}^{j} W'_{j} + \text{POS}$$
(7)

We use a transformer encoder which employs multi-headed self-attention (Vaswani et al., 2017) along with a feed-forward network to obtain the encoded representations for the input fused embedding *F*. Average pooling is applied to the output of the transformer before passing through two dense layers (MLP) to produce the output  $y = MLP(F) = f_{\theta}(X)$ , where  $f_{\theta}(\cdot)$  represents the complete model architecture with parameters  $\theta$ .

#### 3.4. SH-Mix: Components

Given multimodal examples  $X_A$  and  $X_B$ , we embed each modality as:  $X_A = [\mathcal{M}_A^1, \mathcal{M}_A^2, \dots, \mathcal{M}_A^N]$  and  $X_B = [\mathcal{M}_B^1, \mathcal{M}_B^2, \dots, \mathcal{M}_B^N]$ . To compute saliency information at the global and local levels, we also perform a forward pass on the unmixed inputs to obtain an initial unmixed loss  $\mathcal{L}_{org}$  (§3.5).

**Local-Mix** To capture the most important aspects of a given modality, and keep the mixed sample more closely related to the output, modality-specific Mixup is applied to generate the mixed multimodal input  $\tilde{X}$ . We find the saliency  $S_A^i$  of modality  $\mathcal{M}_A^i$  and  $S_B^i$  of  $\mathcal{M}_B^i$  as,

$$S_A^i = \operatorname{sal}(\mathcal{M}_A^i; \mathcal{L}_{org}); S_B^i = \operatorname{sal}(\mathcal{M}_B^i; \mathcal{L}_{org})$$

where  $S_A^i = [(s_1^i)_A, (s_2^i)_A, \dots, (s_n^i)_A]$  and  $S_B^i = [(s_1^i)_B, (s_2^i)_B, \dots, (s_n^i)_B]$ . For  $(m_j^i)_A \in \mathcal{M}_A^i$  and  $(m_j^i)_B \in \mathcal{M}_B^i$ , we find positions of the  $k_i$  greatest values in  $(s_j^i)_A$  and the  $k_i$  least values in  $(s_j^i)_B$ .



Figure 3: **Local-Mix**: Given any audio/text utterance  $m_A$  and  $m_B$  for input samples A and B, we mix the most salient portions of  $m_A$  with the least salient portions of  $m_B$  while zeroing out the remaining features to obtain the mixed utterance  $\tilde{m}$ . More salient features are darker.

Here  $k_i = \delta_{loc} \cdot p_i$ , where  $p_i$  is the number of features in the embedding corresponding to the *i*<sup>th</sup> modality and  $\delta_{loc}$  is a hyperparameter for controlling the local Mixup threshold. We perform Mixup on the features present at these positions. We define binary masks  $(mask_j^i)_A$  and  $(mask_j^i)_B$  of size  $p_i$ .  $(mask_j^i)_A$  is 1 at  $k_i$  most salient positions of  $(m_j^i)_A$  and  $(mask_j^i)_B$ . These masks are used to zero out the features that are not involved in Mixup. We then define Local-Mix as,

$$\tilde{m}_{j}^{i} = \lambda_{loc}(m_{j}^{i})_{A} \odot (mask_{j}^{i})_{A}$$

$$+ (1 - \lambda_{loc})(m_{j}^{i})_{B} \odot (mask_{j}^{i})_{B}$$
(8)

$$\tilde{\mathcal{M}}^i = [\tilde{m}_1^i, \tilde{m}_2^i, \dots, \tilde{m}_n^i]$$
(9)

$$= [\tilde{\mathcal{M}}^{1}, \tilde{\mathcal{M}}^{2}, \dots, \tilde{\mathcal{M}}^{N}]$$

$$= [\tilde{\mathcal{M}}^{1}, \tilde{\mathcal{M}}^{2}, \dots, \tilde{\mathcal{M}}^{N}]$$

$$(10)$$

where  $\lambda_{loc}$  is the local mixing ratio and is sampled from a beta distribution. The labels associated with examples  $X_A$  and  $X_B$  i.e.  $y_A$  and  $y_B$  are also



Figure 4: **Global-Mix**: Given fused representations  $F_A$  and  $F_B$  of input samples A and B, we replace the most salient span in  $F_A$  with the least salient span in  $F_B$  to obtain the mixed fused representation  $\vec{F}$ . More salient utterances are colored darker.

mixed to obtain the mixed label  $\tilde{y}_{\text{loc}}$ .

$$\tilde{y}_{\mathsf{loc}} = \lambda_{\mathsf{loc}} y_A + (1 - \lambda_{\mathsf{loc}}) y_B \tag{11}$$

**Global-Mix** Span Mixup approaches have shown to be more effective in preserving the locality and maintaining the structural coherence of the inputs (Yun et al., 2019); synergistically integrated with saliency-driven methods it has shown to effectively utilize the ingrained local statistics in the data (Kim et al., 2020a). Global-Mix uses the fused representation of the data to enable efficient crossmodal information exchange and leverage these contextual embeddings. For each example  $X_A$ and  $X_B$ , we compute utterance-level saliency for their fused representation  $F_A = [u_1, u_2, ..., u_n]$  and  $F_B = [u'_1, u'_2, ..., u'_n]$  obtained using ADMF, given as,

$$S_A = \operatorname{sal}(F_A; \mathcal{L}_{org}) \; ; \; S_B = \operatorname{sal}(F_B; \mathcal{L}_{org})$$
 (12)

where  $S_A = [(s_1)_A, (s_2)_A, \dots, (s_n)_A]$  and  $S_B = [(s_1)_B, (s_2)_B, \dots, (s_n)_B]$ . We compute the spanlevel saliency of span *p* to *q* as the sum of  $L_1$  norm of the saliencies in the span, given as,

$$s_A[p;q] = \sum_{k=p}^{q} \|(s_k)_A\|_{L_1}$$
(13)

$$s_B[p;q] = \sum_{k=p}^{q} ||(s_k)_B||_{L_1}$$
(14)

As shown in Figure 4, on a span of length  $l = \lambda_{glob} \cdot n$  between inputs  $X_A$  and  $X_B$ , we replace the most salient span [i; i+l-1] in  $F_A$  with the least

salient span [j; j + l - 1] in  $F_B$  as,

ŀ

$$i = \underset{i}{\operatorname{arg\,max}} \ s_A[i; i+l-1] \tag{15}$$

$$j = \arg\min_{i} s_B[j; j+l-1]$$
(16)

$$\widetilde{\mathcal{F}} = \mathsf{globmix}(F_A, F_B, \mathcal{L}_{org})$$
$$= \begin{cases} u'_k & k \notin [j, j+1, \dots j+l-1] \\ u_{i+k-j} & k \in [j, j+1, \dots j+l-1] \end{cases}$$
(17)

The labels associated with examples  $X_A$  and  $X_B$  i.e.  $y_A$  and  $y_B$  are mixed with the global mixing ratio  $\lambda_{glob}$  to obtain the mixed label  $\tilde{y}_{glob}$ ,

$$\tilde{y}_{glob} = \lambda_{glob} \cdot y_A + (1 - \lambda_{glob}) \cdot y_B$$
 (18)

#### 3.5. SH-Mix Traning Objective

The unmixed inputs  $[X_1, X_2, ..., X_N]$  are passed through the model  $f_{\theta}(\cdot)$  to get the corresponding logit  $y'_{\text{org}}$ .  $\mathcal{L}_{\text{org}}$  is computed as the binary cross entropy (BCE) loss between the predicted logit  $y'_{\text{org}}$ and the ground truth  $y_{\text{org}}$ .

$$y'_{\text{org}} = f_{\theta}(X)$$
;  $\mathcal{L}_{\text{org}} = \text{BCE}(y'_{\text{org}}, y_{\text{org}})$  (19)

We perform backpropagation on the loss obtained above to get gradients w.r.t. all the input modalities  $\mathcal{M}^1$  through  $\mathcal{M}^N$  as well as the fused embedding *F* described in equation 7.

For any two unmixed input examples  $X_A$  and  $X_B$ , we perform Local-Mix to get the mixed input  $\tilde{X} = \text{locmix}(X_A, X_B, \mathcal{L}_{org})$  and  $\tilde{y}_{\text{loc}}$ . We pass  $\tilde{X}$  through the model and compute the BCE loss with the output  $y'_{\text{loc}}$  to get the loss  $\mathcal{L}_{\text{loc}}$ 

$$y'_{\text{loc}} = f_{\theta}(\tilde{X}) \quad ; \quad \mathcal{L}_{\text{loc}} = \text{BCE}\left(y'_{\text{loc}}, \tilde{y}_{\text{loc}}\right)$$
(20)

We similarly perform Global-Mix on  $X_A$  and  $X_B$  to get mixed fused embedding  $\tilde{F} =$  globmix( $X_A, X_B, \mathcal{L}_{org}$ ) and mixed label  $\tilde{y}_{glob}$ . We now pass  $\tilde{F}$  into the transformer encoder to get  $y'_{glob}$  and find the BCE loss with  $\tilde{y}_{glob}$  to get the Global-Mix loss  $\mathcal{L}_{glob} = BCE(y'_{glob}, \tilde{y}_{glob})$ . The three losses are combined to get a single weighted loss

$$\mathcal{L} = \alpha \cdot \mathcal{L}_{\text{org}} + \beta \cdot \mathcal{L}_{\text{loc}} + \gamma \cdot \mathcal{L}_{\text{glob}}$$
(21)

#### 4. Experiments

#### 4.1. Datasets

Multimodal Multi-Speaker Merger & Acquisition Call (M&A Calls) (Sawhney et al., 2021) consists of 812 M&A conference calls between 2016 to 2020. The data for each call comprises of the text transcript and the aligned audio recording of the

Model	M&A Calls Dataset					MAEC Dataset						
	τ	= 3	τ	= 7	τ	= 15	τ	= 3	τ	= 7	τ	= 15
Metric	F1 <sub>3</sub>	MCC <sub>3</sub>	$F1_7$	MCC <sub>7</sub>	F1 <sub>15</sub>	MCC <sub>15</sub>	F1 <sub>3</sub>	MCC <sub>3</sub>	F1 <sub>7</sub>	MCC <sub>7</sub>	F1 <sub>15</sub>	$MCC_{15}$
MLP	0.52	0.10	0.57	0.17	0.48	-0.04	0.50	0.09	0.55	0.13	0.55	0.10
LSTM	0.58	0.15	0.54	0.12	0.51	0.11	0.54	0.16	0.50	0.01	0.56	0.12
MulT	0.57	0.18	0.57	0.18	0.52	0.12	0.55	0.13	0.55	0.10	0.54	0.09
MDRM	0.57	0.20	0.58	0.19	0.46	0.11	0.60	0.20	0.54	0.11	0.56	0.13
M3ANet	0.59	0.18	0.58	0.17	0.50	0.13	0.56	0.13	0.54	0.09	0.55	0.10
M3ANet + Mixup	0.58	0.17	0.60	0.21	0.57	0.15	0.56	0.12	0.56	0.12	0.56	0.12
PISA	0.59	0.19	0.61	0.18	0.55	0.14	0.57	0.15	0.55	0.11	0.54	0.12
SH-Mix (Ours)	0.66*	<b>0.32</b> <sup>*</sup>	<b>0.63</b> <sup>*</sup>	0.30 <sup>*</sup>	0.63*	0.26*	0.58	0.18	<b>0.58</b> <sup>*</sup>	<b>0.17</b> <sup>*</sup>	0.56 <sup>*</sup>	0.13 <sup>*</sup>

Table 1: Performance comparison of SH-Mix with both non-transformer and transformer-based baselines for M&A calls and MAEC dataset for price movement prediction  $\tau$  days after the call where  $\tau \in \{3, 7, 15\}$ . \* shows statistically significant improvements (p < 0.005) over PISA under Wilcoxon's Signed Rank Test. **Bold**, *italics* shows the **best**, *second best* performance.

call along with the speaker ID associated with each utterance. We encode text transcripts using BERT (Devlin et al., 2019) and process audio recording using OpenSMILE<sup>2</sup>. We use the train-test split as released with the dataset.

**Multimodal Aligned Earnings Call (MAEC)** (Li et al., 2020) contains aligned text transcripts and associated audio recordings from the earnings calls of S&P 1500 companies between 2015 to 2018. For each example, the text is processed using BERT encoder and the corresponding audio recording is processed using *Praat* (Boersma and Van Heuven, 2001). We use 860 data samples with a training:validation:test split ratio as 60 : 10 : 30, same as the released dataset.

## 4.2. Baseline Models

We compare SH-Mix with several conventional and contemporary multimodal and mixup-based base-lines:

**MLP** The encoding corresponding to each modality is averaged along the time axis and simply concatenated before passing through a vanilla multi-layer perceptron network.

**LSTM** Inputs multimodal time series to individual LSTMs (Hochreiter and Schmidhuber, 1997) and averages before making the final prediction using a dense layer.

**MulT** (Tsai et al., 2019) fuses multimodal sequences using directional pairwise cross-modal transformers followed by sequence models for predictions.

**MDRM** (Qin and Yang, 2019) uses a contextual BiL-STM (Poria et al., 2017) to derive context-aware unimodal sequence representations, which are then fused together using another layer of BiLSTM to extract multimodal inter-dependencies. **M3ANet** (Sawhney et al., 2021) employs attention weights for multimodal fusion, capturing interdependency between modalities utilizing multihead attention to model long-range dependencies and incorporate local and global contextual information.

**M3ANet + Mixup** Simple linear Mixup (Zhang et al., 2018) is performed at the individual modality level before feeding it to M3ANet model. The mixing ratio is sampled out of a beta distribution.

**PISA** (Sawhney et al., 2022a) Current state-of-theart among saliency-based approaches. Applies a portion-wise Mixup method that leverages the hyperbolic space to model complex hierarchies in the data. Since PISA operates on a single modality, we fuse the individual modalities before feeding the inputs to the model.

## 4.3. Training Setup

The architecture of ADMF consists of a hidden layer of size 32 with ReLU activation. We use a transformer block with a feed-forward layer size of 64 with 3 attention heads for M&A calls and 4 attention heads for the MAEC dataset. The batch size for all our experiments is 64. We have used Keras<sup>3</sup> for our implementation. We report the weighted F-1 score and MCC as the mean of 10 independent runs.

We tune the hyper-parameters using Optuna<sup>4</sup> framework. The Mixup-related parameters are tuned by sampling from the following ranges: Global-Mix ratio  $\lambda_{glob} \in [0.1, 0.9]$ , Local-Mix threshold  $\delta_{loc} \in [0.1, 0.9]$ ,  $\alpha \in [0, 1]$ ,  $\beta \in [0, 1]$ ,  $\gamma \in [0, 1]$ , and the initial learning rate  $\in [1e - 4, 2e - 3]$  optimized with Adam optimizer. We use TPE (Treestructured Parzen Estimator) algorithm (Bergstra et al., 2011) as the sampling strategy for hyper-

<sup>3</sup>https://keras.io/ <sup>4</sup>https://optuna.org/

Hyperparameter	M&A Dataset			MAEC Dataset			
	$\tau = 3$	$\tau = 7$	$\tau = 15$	$\tau = 3$	$\tau = 7$	$\tau = 15$	
Global-Mix ratio ( $\lambda_{qlob}$ )	0.38	0.26	0.56	0.23	0.32	0.32	
Local-Mix threshold ( $\delta_{loc}$ )	0.80	0.50	0.53	0.59	0.65	0.55	
Loss coefficient for $\mathcal{L}_{org}(\alpha)$	0.20	0.87	0.10	0.13	0.58	0.15	
Loss coefficient for $\mathcal{L}_{loc}(\beta)$	0.16	0.19	0.22	0.10	0.62	0.29	
Loss coefficient for $\mathcal{L}_{glob}(\gamma)$	0.14	0.12	0.14	0.66	0.26	0.17	
Initial learning rate	7e-4	1e - 4	1.6e - 3	1.1e - 3	9e - 4	1e - 3	

Table 2: Hyperparameter optimization results

parameter tuning. Table 2 provides the details for the best hyperparameters obtained for our model for price movement prediction task on M&A calls and MAEC dataset  $\tau$  days after the call where  $\tau \in \{3, 7, 15\}.$ 

### 4.4. Infrastructure and Compute details

Our model has 105,932 trainable parameters for M&A calls dataset and 48,710 trainable parameters for MAEC dataset. To generate text embeddings, we use a pre-trained BERT base model (uncased), which has 110 million parameters. We run our experiments on one NVIDIA A2 GPU which has 16 GB memory. The total number of GPU hours are 816 hours across all the experiments.

## 4.5. Evaluation Metrics

Following prior work (Mathur et al., 2022b; Sawhney et al., 2021) and given the data imbalance, we use weighted F1-score and Matthews correlation coefficient (MCC) (Matthews, 1975). MCC also mitigates the impact of class distribution skew and is invariant to the class labels.

## 5. Results and Discussion

### 5.1. Performance Comparison

Table 1 shows our model's performance on the financial datasets against the baselines. Models like MLP and LSTM perform feature aggregation over time series/modalities, and MDRM (Qin and Yang, 2019) uses hierarchical multimodal fusion on top of a contextual LSTM (Poria et al., 2017), giving a better representation of individual modalities with temporal dependencies. MulT (Tsai et al., 2019) attends to low-level features and captures long-range dependencies across modalities, thus exhibiting improved performance over these feature aggregation based models. Attention-based transformer models like M3ANet (Sawhney et al., 2021) are able to focus on the relevant parts of an input sequence while also preserving long-range dependencies, thus outperforming the other baselines (Wu et al., 2021; Tsai et al., 2019; Xu et al., 2023; Mathur et al., 2022b). Addition of Mixup to M3ANet further boosts its performance corroborating Mixup's regularization and data augmentation benefits in improving generalization in cases of feature diversity (Carratino et al., 2022). The incorporation of saliency information, utilized in the hyperbolic space for capturing complex geometries, to selectively perform portion-wise mixup in PISA yields performance improvement. Our proposed SH-Mix shows significant performance improvement over existing multimodal baselines, surpassing state-of-the-art by 3 - 7%. These observations verify our hypothesis that SH-Mix is able to select relevant multimodal features across different modalities and timestamps due to hierarchical saliency-guided components that interpolate discriminative temporal spans closely related to the prediction. Further, it also preserves local features key to modeling sequential information similar to Yoon et al. (2021); Kim et al. (2020a). We attribute the gains to the saliency-driven modality-specific nature of interactions in SH-Mix arising due to finegrained local and global Mixup at the embedding level.

## 5.2. Ablation: Impact of Saliency

In Table 3, we conduct an ablation analysis to investigate the contribution of local and global saliency Mixup. We observe that omitting local saliency lowers performance as the model is unable to utilize fine-grained, modality-specific features. Removing global saliency Mixup also leads to performance degradation due to the loss of contextaware fused representations which are crucial for capturing high-level cross-modal dependencies. SH-Mix, combining both global and local saliency, achieves superior performance as it effectively exploits the locally discriminative features in each modality while also capturing broader contextual relationships across the input token sequence. This combined approach brings diversity and qualitative enrichment, resulting in improved generalization.

Saliency Component	M&A	Calls	MAEC		
Saliency Component	F1 <sub>3</sub>	MCC <sub>3</sub>	F1 <sub>3</sub>	MCC <sub>3</sub>	
All (SH-Mix)	0.66*	<b>0.32</b> <sup>*</sup>	<b>0.58</b> <sup>*</sup>	0.18 <sup>*</sup>	
(×) Saliency (Local) (×) Saliency (Global)		0.18 0.19		0.11 0.14	

Table 3: Ablation study covering performance impact of the removal of each kind of saliency component i.e. local and global level Mixup ( $\tau = 3$  days). The combined model with both components shows the best results. \* shows statistically significant improvements (p < 0.005) over other configurations under Wilcoxon's Signed Rank Test. **Bold** shows the **best** performance.

Modality	M&A	Calls	MAEC		
wodanty	F1 <sub>3</sub>	MCC <sub>3</sub>	F1 <sub>3</sub>	MCC <sub>3</sub>	
Only Audio (A)	0.52	0.07	0.53	0.08	
Only Text (T)	0.59	0.19	0.54	0.10	
Audio + Text (AT)	0.66 <sup>*</sup>	0.32 <sup>*</sup>	0.58 <sup>*</sup>	0.18 <sup>*</sup>	

Table 4: Impact of Modality: Text-based (T) unimodal model gives better performance compared to audio-based (A) unimodal model due to noise in acoustic inputs. Combining both modalities (T+A) gives the best performance.\* shows statistically significant improvements (p < 0.005) over other configurations under Wilcoxon's Signed Rank Test. **Bold** shows the **best** performance.

### 5.3. Impact of Modality

Table 4 compares the multimodal saliency-guided Mixup model (AT) with its unimodal counterparts (A, T). We observe that SH-Mix (T) outperforms SH-Mix (A), which can be attributed to the inherent noise and variability in audio data (Mathur et al., 2022a; Chorowski et al., 2015), showing that saliency information extracted from an explicit semantic representation of text is more relevant to the task. We note that SH-Mix significantly outperforms its unimodal variants as multimodality helps to leverage complementary strengths of text utterances and acoustic features, similar to prior works Tsai et al. (2019); Mathur et al. (2022b).

### 5.4. Impact of Augmentation Strength

We observe optimal performance surfaces in the region characterized by both high  $\delta_{loc}$  and high  $\lambda_{glob}$  (Figure 5a). A higher threshold  $\delta_{loc}$  effectively selects the most salient, discriminative features for Local-Mix and a higher mixing ratio  $\lambda_{glob}$  prioritizes longer informative spans (Sawhney et al., 2022a), enhancing global Mixup quality by incorporating rich cross-modal contextual information. Consequently, reduced values for both exhibit a discernible performance drop. Figure 5b reaffirms



Figure 5: Joint and individual impact of Global-Mix mixing ratio ( $\lambda_{glob}$ ) and Local-Mix threshold ( $\delta_{loc}$ ) on SH-Mix's performance on M&A calls. Higher  $\lambda_{glob}$  and  $\delta_{loc}$  boost performance for both cases.

this trend, wherein increasing both  $\lambda_{glob}$  and  $\delta_{loc}$  independently positively impact model performance. Note that other regions with optimal performance also exist as is evident from Figure 5a, e.g. high  $\delta_{loc}$  and low  $\lambda_{glob}$ , which is also the configuration captured during hyperparameter tuning.

Model Setup	MUS	tARD	CMU-MOSI		
Model Setup	<b>F</b> 1	MCC	F1	MCC	
ADMF	0.65	0.28	0.75	0.50	
ADMF + Mixup	0.68	0.35	0.76	0.52	
SH-Mix (Ours)	0.71*	<b>0.41</b> <sup>*</sup>	<b>0.78</b> <sup>*</sup>	<b>0.54</b> <sup>*</sup>	

Table 5: Modality agnostic generalizability: Performance of SH-Mix on audio, text, and video modalities in MUStARD and CMU-MOSI. SH-Mix outperforms ADMF and ADMF + Mixup.\* shows statistically significant improvements (p < 0.005) over other configurations under Wilcoxon's Signed Rank Test. **Bold** shows the **best** performance.

## 5.5. General Applicability of SH-Mix

To gauge the adaptability of SH-Mix to diverse applications, we apply it to sarcasm detection and sentiment analysis binary classification tasks on the MUStARD (Castro et al., 2019) and CMU-MOSI (Zadeh et al., 2016) dataset respectively. Both of these comprise audio, visual and textual sequences. Table 5 shows the effectiveness of SH-Mix over general fusion-based models and vanilla Mixup techniques. It also displays a modelagnostic behaviour, exhibiting performance improvement when applied over different neural baselines (see Table 6). By synergizing the hierarchy with saliency, SH-Mix leverages discriminative modality-specific features and informative global spans, thus establishing it as a comprehensive hierarchical multimodal sequence learning Mixup framework.

Madal Catur	M&A	Calls	MAEC		
Model Setup	F1	MCC	F1	MCC	
MDRM	0.57	0.20	0.60	0.20	
SH-Mix (MDRM)	0.61 <sup>*</sup>	0.23 <sup>*</sup>	0.61 <sup>*</sup>	0.21 <sup>*</sup>	
M3ANet	0.58	0.17	0.56	0.12	
SH-Mix (M3ANet)	0.63*	0.26 <sup>*</sup>	0.56 <sup>*</sup>	0.13 <sup>*</sup>	

Table 6: SH-Mix is generalizable across neural architectures like MDRM and M3ANet.\* shows statistically significant improvements (p < 0.005) over other configurations under Wilcoxon's Signed Rank Test. **Bold** shows the **best** performance.

### 6. Conclusion

Building on the current limitations in multimodal augmentation strategies, we introduced SH-Mix: a saliency-guided hierarchical Mixup technique for multimodal financial prediction tasks. SH-Mix combines multi-level embedding Mixup strategies based on the contribution of each modality and contextual subsequences. Experimental results show that it outperforms the existing state of the art by 3-7%. We further analyze the contribution of local and global levels of saliency, evaluate the impact of each modality and assess the impact of augmentation strength within SH-Mix. We also show that SH-Mix is generalizable across different modalities and neural models

## 7. Ethical Considerations and Limitations

Our research specifically hones in on conference calls in which companies make both transcripts and audio recordings publicly accessible. The data for M&A calls and Earnings conference calls is openly available for anyone to download. Our usage and storage of all the company data strictly adheres to privacy laws, with no collection of personal data or violations.

**Limitations** We acknowledge the presence of gender bias in our study caused by the speakerlevel gender imbalance in the M&A calls and Earnings calls. We also acknowledge the presence of demographic bias in our study since the calls belong to companies in the United States of America and cannot be generalized to other geographies and non-native speakers. Also, our study is limited to English language motivating similar study on other multilingual calls.

**Potential Risks** It is also crucial to note that our work of exploratory research should not be treated as explicit financial advice. All investment-related decisions involve exposure to market risks and should only be taken following thorough evaluation.

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