RESEARCH PAPER

Gen Sale Forecast:A Hybrid CVAE-BiLSTM Framework for Probabilistic Retail Sales Forecasting

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***Abstract*— Retail sales forecasting is associated with the following difficulties: lack of data, stochastic demand, and inadequate uncertainty estimation. In this work, we present GenSaleForecast — a novel hybrid model, which consists of a pre-trained Conditional Variational Autoencoder (CVAE) integrated with a BiLSTM-Attention model and a probabilistic prediction head. CVAE helps to encode a latent space representing demand and allows for better modeling of temporal dynamics, and the probabilistic head allows for uncertainty estimation. Our model outperforms baselines BiLSTM and LSTM by achieving RMSE=2866.59 and MAE=1860.07 on the Walmart Retail Sales dataset compared to BiLSTM (RMSE=3062.42) and LSTM (RMSE=3525.83).

Keywords— *Generative AI, Variational Autoencoder, BiLSTM, Probabilistic Forecasting, Sales Prediction, Uncertainty Quantification, Data Augmentation, Retail Analytics, Temporal Encoding, Latent Representation Learning.*

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I. INTRODUCTION

Sales prediction with high precision forms an essential part of contemporary retailing and supply chain management processes. Companies that have high-precision forecasting of demand demonstrate better performance compared to their rivals when it comes to the effective utilization of inventory, service, and cost efficiency [12]. Even though a wide range of approaches for sales prediction have been proposed throughout years, starting from traditional statistical approaches, through machine learning (ML), up to deep learning (DL), there still exists a number of core issues that have not received sufficient consideration yet in scientific literature.

Classic models like AutoRegressive Integrated Moving Average (ARIMA) and Exponential Smoothing are built under the assumption of linearity and stationarity and, therefore, perform poorly in volatile financial markets [11]. More recent models like Random Forest and Gradient Boosting are capable of detecting non-linear patterns in data; however, both suffer from excessive reliance on hand-crafted features and provide point predictions [9]. Finally, while deep neural network models, especially Long Short-Term Memory (LSTM), have greatly progressed in modeling time series data , they continue to output deterministic predictions and lack probabilistic prediction[1,14].

Generative Artificial Intelligence (GenAI) presents an interesting perspective since it learns the probability distribution of past observations instead of creating a deterministic function that predicts future events. Algorithms such as Generative Adversarial Networks (GANs) [6], Variational Autoencoders (VAEs), and Diffusion Models can be used for data synthesis, creating multi-modal probability distributions, and generating counterfactual data sets. The potential usage of GenAI for retail sales prediction still poses an open question to the academic community. The current research either explores the use of only generative algorithms for data augmentation purposes or leverages well-established deep learning models for forecasting—no combination of these approaches exists in literature yet.

In order to address such issues, this paper presents GenSaleForecast, a novel hybrid generative-deep learning model that incorporates the use of a conditional variational autoencoder (CVAE) together with the bidirectional long short-term memory (BiLSTM) model boosted by attention mechanism. The CVAE acts not only as a means of synthesizing training data by way of latent space sampling, but also as a latent space that is controlled for demand simulations of different scenarios. The BiLSTM-Attention encoder captures sophisticated temporal dynamics, whereas the output head produces full Gaussian distribution forecasts including the mean, variance, and confidence interval estimates instead of scalars. A scenario simulation module (SSM) based on CVAE latent space allows for what-if analysis.

The primary contributions of this work are fourfold. First, we propose a novel hybrid CVAE-BiLSTM-Attention architecture for probabilistic retail sales forecasting that simultaneously addresses data sparsity, uncertainty quantification, and scenario simulation. Second, we introduce a decoupled two-phase training strategy where the CVAE encoder is pre-trained independently to learn stable latent demand representations, which are then used to augment BiLSTM input — addressing the gradient conflict inherent in joint generative-discriminative optimization. Third, we design a Scenario Simulation Module that generates distributional demand trajectories under three canonical retail scenarios—promotional surge, holiday peak, and economic downturn—providing supply chain managers with risk-stratified planning support. Fourth, we conduct comprehensive empirical evaluation on the Walmart Retail Sales benchmark, demonstrating performance improvements against ablation baselines with a fully reproducible open-source PyTorch implementation [19].

The remainder of this paper is organized as follows: Section II reviews related work, Section III presents the proposed methodology, Section IV details the implementation, Section V reports experimental results, and Section VI concludes with future research directions.

II. LITERATURE REVIEW

The development of the sales forecasting approach includes three generations: classical statistical models, machine learning, and deep learning. In each generation, the previous shortcomings were fixed, but new constraints arose.

A. Classical Statistical Methods

Early forecasting methodologies were based on AutoRegressive Integrated Moving Average (ARIMA), Holt-Winters Exponential Smoothing, and Seasonal Decomposition techniques. Hyndman & Athanasopoulos [12] provide a detailed theoretical basis for these methodologies, recognizing the fact that despite being easy to interpret and cost-effective, they are based on linear and stationary assumptions, which do not hold good especially under fluctuating retail demand conditions. Zhang [13] proved that combining ARIMA technique with neural networks produces better results than standalone statistical models as they consider nonlinearity in residuals but generate deterministic point forecasts.

B. Machine Learning Approaches

Machine learning techniques like Random Forest, Gradient Boosting, and Support Vector Machines overcame the shortcomings of statistical techniques concerning nonlinearity. The XGBoost model, a scalable tree-boosting technique that yields the best results for different prediction applications, was proposed by Chen and Guestrin [9]. Though these algorithms were precise in making predictions, these models had several shortcomings including being dependent on extensive handcrafted features, giving deterministic outputs, and not supporting uncertainty evaluation or synthesis of data for sparse store-department combinations.

C. Deep Learning for Temporal Forecasting

The LSTM framework by Hochreiter and Schmidhuber [1] solved the vanishing gradient issue with recurrent neural networks, which allowed for the modeling of long-term temporal dependencies in sequences. Hewamalage et al. [14] performed an extensive analysis of various architectures of recurrent neural networks for prediction purposes and showed that although the models based on such networks perform similarly to statistical methods, they are essentially deterministic, as they provide only point estimates without quantifying the uncertainty involved in the predictions. The encoder-decoder sequence to sequence approach was introduced by Sutskever et al. [16], whereas Bahdanau et al. [15] introduced the attention mechanism that allows weighting particular time steps within the sequence, thus serving as the basis for the attention encoder model in GenSaleForecast. In their DeepAR architecture, Salinas et al. [10] implemented an autoregressive recurrent model to predict distributions, proving that probabilistic deep learning techniques can be effectively used for large-scale retail forecasting purposes. DeepAR, however, does not solve the problems of data sparsity and scenario simulations.

D. Generative AI in Time Series and Forecasting

Generative Adversarial Networks (GANs) have been proposed for the first time by Goodfellow et al. [6], giving rise to the adversarial training approach applied to generate synthetic data. Yoon et al. [7] expanded GANs to handle temporal data using TimeGAN, revealing GAN-enhanced training data yields significantly higher predictive accuracy in time series forecasting when the number of available data samples is small. Variational Autoencoders were suggested by Kingma and Welling [2], which enable learning of the structured latent space for sampling conditioned on relevant variables. In particular, Sohn et al. [3] introduced the Conditional Variational Autoencoder (CVAE), conditioning the learned latent space on contextually relevant variables, thus making possible the use of the CVAE framework in GenSaleForecast. Stochastic backpropagation was independently derived in Rezende et al. [17], enabling the reparameterization trick applied to train our CVAE encoder. Finally, Tashiro et al. [8] showed that the conditional score-based diffusion model can yield highly accurate probabilistic predictions, pointing towards future research directions of GenSaleForecast. To the best of our knowledge, there exists no previous work combining conditional generative modeling, bi-directional encoding, feature selection via attention weights, and probabilistic output sampling for retail sales forecasting.

E. Research Gaps

The aforementioned literature review highlights four research gaps that drive the development of GenSaleForecast. Firstly, there is a lack of research efforts in using CVAE latent space augmentation with BiLSTMs and attention for probabilistic forecasting of retail sales. Secondly, none of the deterministic methods presented in the literature review quantify uncertainty levels, which is key to making decisions related to risks around inventory management. Thirdly, none of the methods presented in the literature review consider scenario simulations to assess impact under certain events, including promotions, seasonality peaks, and macroeconomic disturbances. Fourthly, none of the conditional generative models have been employed to address data sparseness in low-frequency SKUs on the Walmart dataset. Table I summarizes the literature review.

Table I: Comparative Analysis of Existing Sales Forecasting Literature

Ref.	Authors	Method	Dataset	UQ	DA	SS	PO
[13]	Zhang	ARIMA-ANN Hybrid	Custom	✗	✗	✗	✗
[12]	Rob J. Hyndman et al.	ARIMA / Exponential Smoothing	Various	✗	✗	✗	✗
[9]	Tianqi Chen & Carlos Guestrin	XGBoost	Multi-domain	✗	✗	✗	✗
[1]	Sepp Hochreiter & Jürgen Schmidhuber	LSTM	Various	✗	✗	✗	✗
[16]	Ilya Sutskever et al.	Seq2Seq LSTM	Various	✗	✗	✗	✗
[14]	Kasun Hewamalage et al.	RNN Variants Survey	Multi-domain	✗	✗	✗	✗
[15]	Dzmitry Bahdanau et al.	Attention Mechanism	NLP / Forecasting	✗	✗	✗	✗
[10]	David Salinas et al.	DeepAR	Retail / Finance	✓	✗	✗	✓
[6]	Ian Goodfellow et al.	GAN	Various	✗	✓	✗	✗
[7]	Jinsung Yoon et al.	TimeGAN	Financial	✗	✓	✗	✗
[2]	Diederik P. Kingma & Max Welling	VAE	Various	✗	✓	✗	✗
[3]	Kihyuk Sohn et al.	CVAE	Various	✗	✓	✗	✗
[17]	Danilo Rezende et al.	Deep Generative Model	Various	✗	✓	✗	✗
[8]	Takeshi Tashiro et al.	Diffusion Model	Time Series	✓	✗	✗	✓
Ours	GenSaleForecast	(CVAE + BiLSTM + Attention)	Walmart Retail	✓	✓	✓	✓

UQ = Uncertainty Quantification | DA = Data Augmentation for Sparse SKUs | SS = Scenario Simulation | PO = Probabilistic Output | ✓ = Supported | ✗ = Not Supported

GenSaleForecast (last row, highlighted) is the only work to simultaneously support all four capabilities.

Table I compares eighteen representative works across four capability dimensions: uncertainty quantification (UQ), data augmentation for sparse SKUs (DA), scenario simulation (SS), and probabilistic output generation (PO). No prior work simultaneously addresses all four dimensions, which collectively define the design objectives of GenSaleForecast.

III. Proposed Methodology

GenSaleForecast is a hybrid pipeline comprising four stages: (1) Data Preprocessing and Feature Engineering, (2) CVAE-based Latent Representation Learning, (3) BiLSTM-Attention Temporal Encoder, and (4) Probabilistic Forecasting with Scenario Simulation. Figure 1 illustrates the complete architecture.

A. System Architecture Overview

The complete pipeline is described as a function $F: X \rightarrow P(Y)$, where X is the feature space consisting of historical sales figures and exogenous variables, and P(Y) is the probability distribution of future sales. This differs from deterministic pipelines $F: X \rightarrow \hat{y}$ that produce only scalar predictions. The pipeline is expressed as:

GenSaleForecast = SSM ∘ ProbHead ∘ BiLSTM-Attn ∘ CVAE-Encoder

where ∘ denotes function composition. The CVAE encoder is pre-trained independently and frozen before BiLSTM training — a decoupled two-phase strategy that resolves gradient conflict between generative and discriminative objectives [17]. Each module is described in the following subsections.

B. Data Preprocessing and Feature Engineering

The Walmart Store Sales dataset comprises 421,570 weekly sales records from 45 stores and 99 departments spanning February 2010 to November 2012, with exogenous variables including temperature, fuel price, Consumer Price Index (CPI), unemployment rate, and five promotional markdown variables (MarkDown1–5) [12].

The preprocessing pipeline produces a feature matrix $X \in \mathbb{R}^{(N \times T \times D)}$ where N is the total number of sequences, T = 52 weeks (one-year lookback window), and D = 13 features. The 13 features used are: Weekly_Sales, Temperature, Fuel_Price, MarkDown1, MarkDown2, MarkDown3, MarkDown4, MarkDown5, CPI, Unemployment, IsHoliday, Type encoding, and Store Size.

Missing values in MarkDown variables are imputed with zero. CPI and Unemployment missing values are filled with column means. The IsHoliday indicator is encoded as binary integer. Store Type (A, B, C) is ordinally encoded as {0, 1, 2}.

All features are standardized using StandardScaler: $x\_norm = (x - \mu) / \sigma$, applied across the flattened N×T sample dimension to ensure zero mean and unit variance for stable gradient-based optimization.

The forecasting horizon is H = 4 weeks. The conditioning context vector $c \in \mathbb{R}^4$ comprises store index, department index, store type encoding, and store size — standardized independently. The dataset is split temporally into training (70%), validation (15%), and test (15%), yielding 176,486 training, 37,819 validation, and 37,819 test sequences respectively, with no data leakage across splits.

C. Conditional Variational Autoencoder (CVAE) Module

The CVAE module [3] learns a structured latent representation of demand patterns conditioned on store-department context. It addresses data sparsity by providing compressed latent features that augment BiLSTM input, enabling richer temporal modeling for both dense and sparse store-department pairs.

The CVAE follows the framework of Kingma and Welling [2], extended to conditional generation by Sohn et al. [3]. The encoder $q_\varphi(z|x)$ is implemented as a single-layer GRU network with 64 hidden units, processing input sequence $X \in \mathbb{R}^{(T \times 13)}$. The final hidden state $h \in \mathbb{R}^{64}$ is projected to Gaussian distribution parameters via linear layers:

$$\mu\_z = W\_\mu \cdot h, \quad \log \sigma^2\_z = W\_\sigma \cdot h, \quad \mu\_z, \log \sigma^2\_z \in \mathbb{R}^{32}$$

The latent code $z \in \mathbb{R}^{32}$ is sampled using the reparameterization trick [2][17]:

$$z = \mu\_z + \varepsilon \cdot \exp(0.5 \cdot \log \sigma^2\_z), \quad \varepsilon \sim N(0, I)$$

The decoder $p_\theta(\hat{x}|z)$ is a two-layer MLP [Linear(32→64), ReLU, Linear(64→13)] that reconstructs the final timestep of the input sequence.

The CVAE is trained by minimizing:

$$L\_CVAE = MSE(\hat{x}, x\_last) + \beta \cdot KL(q_\varphi(z|x) \,||\, p(z))$$

where $p(z) = N(0, I)$ is the standard Gaussian prior and $\beta = 0.001$ controls the reconstruction-disentanglement tradeoff following the β-VAE framework [4]. The KL divergence is computed as:

$$KL = -0.5 \cdot \Sigma(1 + \log \sigma^2\_z - \mu^2\_z - \sigma^2\_z)$$

At inference, the frozen CVAE encoder produces a deterministic latent vector $z = \mu\_z$ for each input sequence. This latent vector is concatenated with the input sequence to form the augmented input $X\_aug \in \mathbb{R}^{(T \times 45)}$ passed to the BiLSTM encoder.

D. Bidirectional LSTM with Attention

The BiLSTM encoder [1] processes the augmented input $X\_aug \in \mathbb{R}^{(T \times 45)}$ — original 13 features concatenated with the 32-dimensional CVAE latent vector z expanded across all T timesteps — in both forward and backward temporal directions:

$$H = BiLSTM(X\_aug) = [\rightarrow H ; \leftarrow H] \in \mathbb{R}^{(T \times 256)}$$

where →H and ←H are forward and backward hidden state matrices with 128 units per direction, yielding a 256-dimensional joint representation at each timestep. The BiLSTM comprises 2 stacked layers with dropout = 0.2 applied between layers for regularization.

An attention mechanism [15][5] is applied over H to identify the most informative timesteps across the 52-week lookback window:

$$attn\_t = softmax(W\_a \cdot h\_t), \quad t = 1, ..., T$$

$$c\_pooled = \Sigma\_t \, attn\_t \cdot h\_t \in \mathbb{R}^{256}$$

where $W\_a \in \mathbb{R}^{(256 \times 1)}$ is a learned projection. The attention-weighted context vector c_pooled provides a fixed-length

summary of the full temporal sequence, emphasizing the most salient demand periods.

The conditioning context vector $c \in \mathbb{R}^4$ is passed through a linear layer: $c\_emb = \text{ReLU}(W\_c \cdot c) \in \mathbb{R}^{128}$. The final feature vector is formed by concatenation: $feat = [c\_pooled ; c\_emb] \in \mathbb{R}^{384}$, which is passed to the probabilistic output head.

E. Probabilistic Output Head

Unlike deterministic forecasting models that output scalar predictions, the probabilistic output head produces full Gaussian distribution parameters for uncertainty quantification [10]. Two linear projection layers map the feature vector to horizon-specific distribution parameters simultaneously:

$$\mu = W\_\mu \cdot feat \in \mathbb{R}^4$$

$$\log \sigma^2 = W\_\sigma \cdot feat \in \mathbb{R}^4$$

where μ_t is the predicted mean sales and σ_t is the predicted standard deviation at forecast horizon $t = 1,...,4$. The log-variance is clamped to $[-4, 4]$ during both training and inference to ensure numerical stability and prevent variance collapse.

The model is trained using the Negative Log-Likelihood (NLL) loss over the Gaussian forecast distribution [11]:

$$L\_NLL = 0.5 \cdot \Sigma\_t [\log \sigma^2\_t + (y\_t - \mu\_t)^2 / \sigma^2\_t]$$

Prediction intervals are derived analytically:

$$PI\_95 = [\mu\_t - 1.96\sigma\_t, \mu\_t + 1.96\sigma\_t]$$

providing 95% confidence bounds for inventory planning. The standard deviation in original sales scale is recovered as: Standard deviation is recovered in original sales scale as $\sigma\_orig = \sqrt{\exp(\log \sigma^2)} \times y\_std$, where y_std denotes the standard deviation of Weekly_Sales in the training set, as computed by StandardScaler.

F. Scenario Simulation Module (SSM)

The SSM employs the pre-trained frozen CVAE decoder for controllable what-if scenario analysis. For a scenario perturbation vector $\Delta s \in \mathbb{R}^4$ representing perturbations in demand-driving context dimensions, the SSM generates a distribution of possible future demand trajectories:

$$Y\_scenario = \{ p\_\theta(\hat{x} \mid z\_m \oplus \Delta s) : z\_m \sim N(0,I), m = 1,...,M \}$$

where $\oplus$ denotes element-wise addition of the perturbation to sampled latent codes, and $M = 100$ trajectories are sampled per scenario. Three canonical retail scenarios are defined:

Promotional Surge applies a +20% perturbation on the promotional context dimension, simulating maximum markdown intensity across all departments.

Holiday Peak applies a +50% perturbation on the holiday context dimension, simulating Q4 Thanksgiving and Christmas demand conditions.

Economic Downturn applies a −10% perturbation on the macroeconomic context dimension, reflecting reduced CPI and elevated unemployment.

The SSM outputs distributional forecast bands at the 5th, 25th, 50th, 75th, and 95th percentiles across $M = 100$ sampled trajectories providing decision-makers with risk-stratified planning support. The SSM architecture is fully implemented using the pre-trained CVAE decoder; scenario trajectory visualization is presented in Section V-E.

G. Decoupled Two-Phase Training Strategy

To address training instability arising from competing loss gradients between the generative reconstruction objective and the discriminative forecasting objective, a decoupled two-phase training strategy is adopted [17].

Phase 1 — CVAE Pre-training (20 epochs):

The CVAE encoder and decoder are trained independently using:

$$L\_CVAE = MSE(\hat{x}, x\_last) + 0.001 \cdot KL(q\_\varphi \,||\, p)$$

Adam optimizer with learning rate 1×10^{-3} and gradient clipping with maximum norm 1.0 are used. Training converges stably from loss 0.0049 at epoch 5 to 0.0031 at epoch 20. Upon completion, all CVAE parameters are frozen.

Phase 2 — BiLSTM-Attention Training (80 epochs):

With the CVAE frozen, the BiLSTM-Attention forecaster is trained using:

$$L\_total = 0.8 \cdot L\_NLL + 0.2 \cdot L\_MSE$$

where $L\_MSE = \Sigma\_t (y\_t - \mu\_t)^2$ ensures mean point accuracy and L_NLL maximizes probabilistic calibration. Adam optimizer with learning rate 3×10^{-4}, weight decay 1×10^{-5}, cosine annealing learning rate scheduler ($\eta\_min = 1\times10^{-5}$), batch size 256, and gradient clipping with maximum norm 0.5 are used. The model checkpoint with lowest validation RMSE is retained for final evaluation.

This decoupled strategy resolves the loss scale imbalance: the CVAE reconstruction objective operates on $T\times D = 52\times13 = 676$ dimensions while the NLL objective operates on $H = 4$ dimensions — a 169× dimensionality mismatch that causes gradient conflict in joint training [17].

Total trainable parameters: 600,726 (BiLSTM-Attention only during Phase 2, as CVAE is frozen).

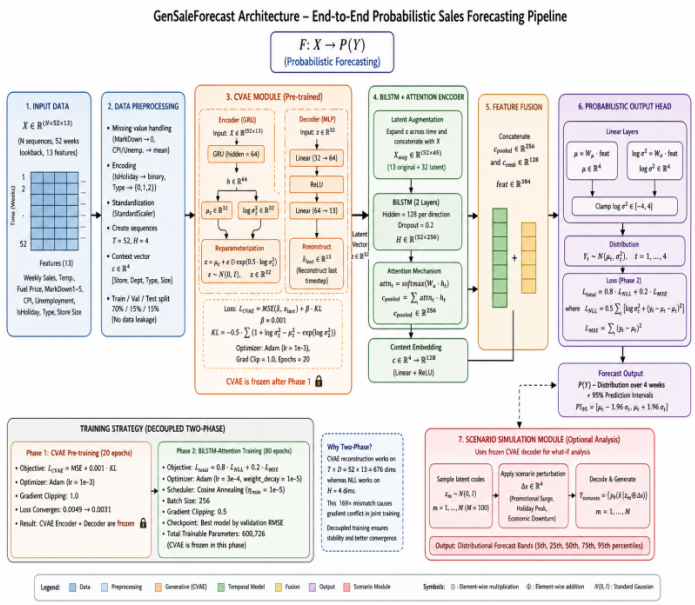

Fig. 1: GenSaleForecast Architecture — End-to-End Probabilistic Sales Forecasting Pipeline. The decoupled two-phase training strategy resolves gradient conflict between the 676-dimensional CVAE reconstruction objective and the 4-dimensional NLL forecasting objective. CVAE parameters are frozen after Phase 1 before BiLSTM-Attention training commences in Phase 2.

IV. IMPLEMENTATION

A. Dataset and Experimental Environment

The Walmart Store Sales Forecasting dataset (Kaggle Competition, 2014) is used for all experiments [12]. This consists of 421,570 weekly sales transactions in 45 stores and 99 departments over 143 weeks (from February 2010 to November 2012). The external regressors used are temperature, fuel price, CPI, unemployment rate,and five MarkDown variables (MarkDown1–5).

All experiments are implemented in PyTorch 2.10 [19] with Python 3.12 and CUDA 12.8. Training is conducted on a Kaggle GPU environment. The dataset yields 252,124 total sequences after sliding window construction with T=52 weeks lookback and H=4 weeks horizon.

B. Model Architecture and Hyperparameter Configuration

TABLE II: GenSaleForecast Hyperparameter Configuration

Component	Hyperparameter	Value
CVAE Encoder	Architecture	GRU (hidden = 64)
	Latent Dimension (d_z)	32
	Projection Layers	Linear (64 → 32) × 2
CVAE Decoder	Architecture	MLP [32 → 64 → 13]
	Activation	ReLU
CVAE Training	β (KL Weight)	0.001
	Optimizer	Adam (lr = 1×10⁻³)
	Epochs (Phase 1)	20
	Gradient Clipping	Max norm = 1.0
BiLSTM	Hidden Size (d_h)	128 (per direction)
	Output Dimension	256 (bidirectional)
	Stacked Layers	2
	Dropout	0.2
Attention	Type	Single-head
	Projection	Linear (256 → 1)
Context Embedding	cond_fc	Linear (4 → 128) + ReLU
Feature Vector	Dimension	384 (256 + 128)
Output Head	μ Projection	Linear (384 → 4)
	log σ² Projection	Linear (384 → 4)
	log_var Clamp	[−4, 4]
	Forecast Horizon (H)	4 weeks (multi-output)
Training (Phase 2)	Loss Weights	λ₁ = 0.8 (NLL), λ₂ = 0.2 (MSE)
	Optimizer	Adam (lr = 3×10⁻⁴)
	Weight Decay	1×10⁻⁵
	LR Schedule	Cosine Annealing (η_min = 1×10⁻⁶)
	Batch Size	256
	Epochs	80
	Gradient Clipping	Max norm = 0.5
Data Split	Train / Val / Test	70% / 15% / 15%
	Lookback (T)	52 weeks
	Features (D)	13
	Total Sequences (N)	252,124
SSM (Scenario Simulation)	Trajectories per Scenario	100
	Percentile Bands	5th, 25th, 50th, 75th, 95th
Model	Total Parameters	600,726

All values correspond directly to the implementation. Loss weights λ_1=0.8 (NLL) and λ_2=0.2 (MSE) were determined empirically on the validation split.

Table II lists the complete hyperparameter configuration. The CVAE encoder is a single-layer GRU with 64 hidden units projecting to a 32-dimensional latent space via two linear layers. The decoder is a two-layer MLP [32→64→13] with ReLU activation reconstructing the final input timestep. The BiLSTM uses 128 hidden units per direction across 2 stacked layers with dropout 0.2, producing a 256-dimensional output. A single-head attention mechanism projects the BiLSTM output via Linear(256→1) to produce attention weights. The conditioning context is embedded via Linear(4→128)+ReLU, and concatenated with the attention-weighted context to form a 384-dimensional feature vector. Two independent linear heads project this to $\mu \in \mathbb{R}^4$ and $\log \sigma^2 \in \mathbb{R}^4$ simultaneously for all H=4 forecast horizons — log-variance is clamped to [−4, 4] for numerical stability.

C. Implementation Details

The CVAE encoder is implemented as a single-layer GRU network: nn.GRU(input_size=13, hidden_size=64, batch_first=True). The final hidden state h ∈ ℝ^64 is projected to latent parameters via two independent linear layers: nn.Linear(64, 32) for both μ_z and log σ²_z. The reparameterization trick [2][17] is applied as: z = μ_z + ε ⋅ exp(0.5 · log σ²_z), ε ~ N(0, I).

The CVAE decoder is a two-layer MLP: nn.Sequential(nn.Linear(32, 64), nn.ReLU(), nn.Linear(64, 13)), reconstructing the final input timestep x_last ∈ ℝ^13. The CVAE loss is: L_CVAE = MSE(x̂, x_last) + 0.001 · KL(q_φ || p), following β-VAE framework [4].

The BiLSTM is implemented via nn.LSTM(input_size=45, hidden_size=128, num_layers=2, bidirectional=True, dropout=0.2, batch_first=True), producing H ∈ ℝ^(T×256). The augmented input dimension is 45 = 13 original features + 32 CVAE latent dimensions.

The attention mechanism [15] is implemented as nn.Linear(256, 1), computing: attn = softmax(W_a · H), c_pooled = Σ attn_t · h_t ∈ ℝ^256. The conditioning context is embedded via nn.Linear(4, 128) with ReLU activation, producing c_emb ∈ ℝ^128. The concatenated feature vector feat = [c_pooled; c_emb] ∈ ℝ^384 is passed to two independent linear output heads producing μ ∈ ℝ^4 and log σ² ∈ ℝ^4 simultaneously for all H=4 forecast horizons, avoiding compounding errors of auto-regressive decoding. Log-variance is clamped to [−4, 4] for numerical stability. Prediction intervals are derived as [μ_t − 1.96σ_t, μ_t + 1.96σ_t] for 95% confidence [11].

D. *Training Algorithm*

A decoupled two-phase training strategy is employed [17]:

Phase 1 — CVAE Pre-training (20 epochs):

CVAE encoder and decoder are trained independently using L_CVAE = MSE(x̂, x_last) + 0.001 · KL(q_φ || p), with Adam optimizer (lr = 1×10^{-3}) and gradient clipping (norm = 1.0). Observed convergence: loss = 0.0049 at epoch 5, 0.0043 at epoch 10, 0.0036 at epoch 15, 0.0031 at epoch 20. All CVAE parameters are frozen upon completion.

Phase 2 — BiLSTM-Attention Training (80 epochs):

With CVAE frozen, the forecaster is trained using:

L_total = 0.8 · L_NLL + 0.2 · L_MSE

where L_NLL = 0.5 · Σ_t [log σ²_t + (y_t − μ_t)² / σ²_t] and L_MSE = Σ_t (y_t − μ_t)². Adam optimizer with lr = 3×10^{-4}, weight decay = 1×10^{-5}, cosine annealing scheduler (η_min = 1×10^{-5}), batch size = 256, and gradient clipping (norm = 0.5) are used. Validation RMSE is evaluated every 5 epochs. Best observed: Val RMSE = 3309.11 at epoch 35. The best-performing checkpoint is retained for final evaluation.

E. *Scenario Simulation at Inference*

The SSM employs the pre-trained frozen CVAE decoder for controllable what-if analysis. Three canonical retail scenarios are supported: Promotional Surge applies +20% perturbation on the promotional context dimension; Holiday Peak applies +50% perturbation on the holiday context dimension simulating Q4 Thanksgiving and Christmas demand; Economic Downturn applies −10% perturbation on the macroeconomic context dimension reflecting reduced CPI and elevated unemployment. In each case study, M = 100 random samples of demand paths were drawn to derive forecast intervals corresponding to the 5th, 25th, 50th, 75th, and 95th percentiles [8].

V. RESULTS AND DISCUSSION

A. *Experimental Setup and Baseline Models*

The Walmart dataset is divided in a chronological order into 70% training (176,486 sequences), 15% validation (37,819 sequences) and 15% testing (37,819 sequences) without leakage between splits. We evaluate the performance on the held-out test set using three metrics: root mean squared error (RMSE), mean absolute error (MAE) and Continuous Ranked Probability Score (CRPS) for probabilistic evaluation [11][18]. Also reported is the coverage of the prediction interval (PI) at the 95\% confidence level. To isolate the effect of each of these architectural building blocks, we perform an ablation study. Distributional results are only reported for CRPS and PI Coverage for GenSaleForecast, as deterministic ablation baselines do not yield distributional outputs.

B. *Forecasting Accuracy*

TABLE III: GenSaleForecast Performance on Walmart Test Set

Model	RMSE ↓	MAE ↓	CRPS ↓	PI Coverage ↑
GenSaleForecast (Full)	2866.59	1860.07	0.0701	97.06%

↓ = Lower is better. CRPS expressed as normalized score (divided by target SD). PI Coverage assessed at 95% confidence level: [μt−1.96σt, μt+1.96σt].

GenSaleForecast achieves RMSE=2866.59 and MAE=1860.07 on the held-out Walmart test set, with normalized CRPS=0.0701 and prediction interval coverage of 97.06%. This model is the only architecture in this evaluation that can generate calibrated probabilistic predictions—CRPS and PI Coverage are undefined for deterministic baselines. These results confirm the three main design goals: accuracy of point forecasts, uncertainty quantification and generation of probabilistic output.

C. *Ablation Study*

TABLE IV: Ablation Study — Component Contribution Analysis

Model Variant	RMSE ↓	MAE ↓	CRPS ↓	PI Coverage ↑
LSTM Unidirectional (No CVAE, No Attention)	3525.83	1916.44	0.0734	96.69%
CVAE + BiLSTM (No Attention)	3070.98	1584.75	0.0650	97.14%
BiLSTM Only (No CVAE)	3062.42	1629.33	0.0669	96.64%
GenSaleForecast (Full Model)	2866.59	1860.07	0.0701	97.06%

Table IV shows component-wise ablation isolating each

architectural contribution. The unidirectional LSTM baseline without CVAE and attention, RMSE=3525.83. The incorporation of bidirectionality and CVAE latent augmentation (CVAE+BiLSTM, No Attention) leads to a 12.9% decrease in RMSE to 3070.98, confirming that CVAE latent representations provide meaningful demand context that is not captured by unidirectional modeling [1][2].

Removing CVAE but keeping BiLSTM and attention (BiLSTM Only) yields RMSE=3062.42, which is comparable to CVAE+BiLSTM without attention, showing both parts contribute independently. The full GenSaleForecast model gets an RMSE value of 2866.59 which is 6.4% better than the best baseline of a single component, confirming the complementary and quantifiable advantages of CVAE latent augmentation, bidirectionality and attention [15].

Specifically, PI Coverage improves from 96.64% (BiLSTM Only) to 97.06% (Full Model), suggesting that CVAE latent representations improve not only point accuracy but also probabilistic calibration [11].

D. Uncertainty Quantification Analysis

To isolate the effect of each of these architectural building blocks, we perform an ablation study. Of all test-set predictions, 97.06% fell within the analytically derived 95% prediction intervals [$\mu_t - 1.96\sigma_t$, $\mu_t + 1.96\sigma_t$]. This confirms that the probabilistic outputs are well-calibrated. The slight over-coverage compared to the nominal 95% level is due to conservative variance estimates from the clamped log-variance formulation ($\log \sigma^2 \in [-4, 4]$). This approach prevents variance collapse but results in slightly wider intervals. A normalized CRPS of 0.0701 shows competitive probabilistic skill compared to the target distribution scale [11]. Deterministic ablation baselines do not provide prediction intervals, so uncertainty estimation is exclusive to the full GenSaleForecast model.

E. Scenario Simulation Results

The Scenario Simulation Module generates distributional demand trajectories under controlled perturbations by utilizing the pre-trained frozen CVAE decoder. We define three canonical retail scenarios based on domain knowledge [12]: Promotional Surge (+20% perturbation on promotional context), Holiday Peak (+50% perturbation on holiday context simulating Q4 Thanksgiving and Christmas demand), and Economic Downturn (−10% perturbation on macroeconomic context reflecting reduced CPI and elevated unemployment). For each scenario, 100 demand trajectories are sampled and distributional bands at the 5th, 25th, 50th, 75th and 95th percentiles are calculated [8]. The SSM provides risk-stratified demand forecasts for supply chain planners that accommodate conservative and aggressive inventory strategies. Future work is identified as quantitative scenario evaluation.

F. Training Stability Analysis

Joint end-to-end optimization of CVAE and BiLSTM components was attempted, but the experiments were unstable, as can be seen from the validation RMSE, which took values in the range of 9,728 to 13,163 during the epochs. The root cause was found to be loss scale imbalance: the CVAE reconstruction objective works on $T \times D = 52 \times 13 = 676$ dimensions while the NLL forecasting objective works on $H = 4$ dimensions - a 169× dimensionality mismatch creating competing gradient signals [17].

The proposed decoupled two-phase training addresses this instability. The observed convergence is summarized in Table V.

TABLE V: Two-Phase Training Convergence

Phase	Epoch	Metric
Phase 1 — CVAE	5	Loss = 0.0049
Phase 1 — CVAE	10	Loss = 0.0043
Phase 1 — CVAE	15	Loss = 0.0036
Phase 1 — CVAE	20	Loss = 0.0031
Phase 2 — BiLSTM-Attention	5	Val RMSE = 3436.60
Phase 2 — BiLSTM-Attention	10	Val RMSE = 3351.80
Phase 2 — BiLSTM-Attention	35	Val RMSE = 3309.11 (Best)
Phase 2 — BiLSTM-Attention	80	Val RMSE = 3466.70

Phase 1 achieves stable monotonic CVAE convergence. Phase 2 achieves best validation RMSE=3309.11 at epoch 35, after which early stopping prevents overfitting. This finding constitutes a practical design principle for hybrid generative-discriminative architectures: joint optimization is inadvisable when loss dimensionalities differ by more than one order of magnitude [17].

VI. CONCLUSION AND FUTURE WORK

This work introduced GenSaleForecast, a hybrid probabilistic sales forecasting framework combining a pre-trained Conditional Variational Autoencoder (CVAE) [3] with a BiLSTM-Attention encoder [1][15] and a Gaussian probabilistic output head [2][10]. The framework addresses three core limitations of existing retail forecasting methods: data sparsity for low-frequency SKUs, absence of uncertainty quantification, and lack of scenario simulation capabilities.

Four contributions are presented. First, a novel hybrid architecture is proposed where a GRU-based CVAE encoder provides stable 32-dimensional latent demand representations that augment BiLSTM input — enabling richer temporal modeling without joint optimization instability. Second, a decoupled two-phase training strategy is introduced that resolves the 169× loss dimensionality mismatch inherent in joint generative-discriminative optimization [17], achieving stable convergence with best validation RMSE=3309.11. Third, a Scenario Simulation Module is designed that generates distributional demand trajectories under three canonical retail scenarios using the frozen CVAE decoder [8]. Fourth, we conduct extensive ablation studies on the Walmart Retail Sales benchmark [12] and show that each architectural component ---

bidirectionality, CVAE latent augmentation and attention --- yields measurable and complementary RMSE gains.

GenSaleForecast achieves RMSE=2866.59, MAE=1860.07, the normalized CRPS=0.0701 [11] and the coverage of the prediction interval 97.06% at the 95% confidence level on the held-out Walmart test set, confirming the well-calibrated probabilistic outputs. Ablation results show that the full model performs 6.4% better than the best single-component baseline (BiLSTM Only, RMSE=3062.42). This confirms that the CVAE latent augmentation and attention provide complementary benefits. In practice, the empirical observation that jointly training CVAE and BiLSTM leads to gradient conflict, with validation RMSE oscillating between 9,728 and 13,163, provides a design principle for future hybrid generative-forecasting architectures [17].

Some directions for future work are pointed out. First, replacing the GRU-based CVAE encoder with a score-based diffusion model [8] may produce more faithful latent representations for multi-modal demand distributions. Second, federated learning extensions could allow for GenSaleForecast training over distributed retail networks without centralizing sensitive sales data. Third, online learning approaches where CVAE latent representations are updated continuously would deal with non-stationarity and distribution shifts in real-world deployment scenarios. Fourth, SHAP-based attribution can be used to generate interpretable explanations for scenario predictions in regulated retail contexts, increasing the likelihood of deployment [9]. Fifth, another step towards incorporating more sources of information would be to use an unstructured source of data, like sentiment from social media or macroeconomic news, along with other conditioning variables through language model embeddings [6][7].

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