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Deep Learning for Anomaly Detection in CPI Data Across Countries

Introduction

Detecting anomalies in Consumer Price Index (CPI) time series is crucial for identifying unusual economic events (e.g. price shocks, hyperinflation episodes) or data quality issues. An *anomaly* in this context refers to an inflation observation that deviates significantly from expected patterns across time or relative to peer countries. With CPI data available for many countries over decades, researchers have started leveraging state-of-the-art deep learning models to automatically flag such outliers. Deep learning methods can capture complex temporal dynamics and cross-country patterns that traditional statistical outlier tests might miss [1]. In this review, we survey the dominant deep learning architectures used for CPI anomaly detection, typical modeling strategies, common datasets, and key findings from recent studies. We also compare these approaches and discuss their performance, applicability, and the pros and cons of different modeling choices.

Common Deep Learning Models for Economic Anomaly Detection

Modern anomaly detection in time series generally falls into a few broad categories of deep learning models [2]. In the economic domain (including CPI/inflation data), the most commonly used architectures include recurrent networks, autoencoders, and transformers, often adapted for unsupervised or semi-supervised learning:

- **Recurrent Neural Networks (LSTM/GRU):** Recurrent models like Long Short-Term Memory (LSTM) networks are widely used to model CPI trajectories due to their ability to capture temporal dependencies. A typical approach is **forecasting-based anomaly detection** [3]: the RNN (e.g. an LSTM) is trained to predict the next CPI value (or next window of values), and anomalies are flagged when the actual value deviates from the prediction beyond a threshold. This leverages prediction error as an anomaly score [4]. LSTMs have been used for country-specific CPI forecasting, and large prediction errors often coincide with known inflation shocks (e.g. policy changes or supply crises). However, pure forecasting models can struggle if the time series undergoes sudden regime changes [5] – precisely when anomalies occur. Thus, while LSTMs are good at learning regular inflation dynamics, their anomaly detection performance depends on stable patterns. Enhanced variants include using **sequence-to-sequence LSTMs** (encoder-decoder) for multi-step forecasting or incorporating exogenous inputs (like oil prices or exchange rates) to improve prediction of normal CPI movements. Overall, RNN-based methods are effective at capturing short- and medium-term dependencies but may miss long-range context or simultaneously modeling many countries.

- **Autoencoder-Based Models:** Autoencoders form the backbone of **reconstruction-based anomaly detection** [6]. In this setup, a model (often an LSTM Autoencoder for sequence data) is trained to **reconstruct** the input CPI time series (or a sliding window segment of it). The idea is that the autoencoder will reconstruct "normal" patterns with low error, but will fail to accurately reconstruct anomalous patterns, resulting in a high reconstruction error that flags an outlier. *LSTM Autoencoders* have shown strong performance in detecting anomalies in time series data

[7]. For example, a study comparing methods found that an LSTM autoencoder achieved better anomaly detection performance than a straightforward LSTM predictor [7]. The autoencoder's latent space captures the typical inflation dynamics, and when an unusual event (say a one-time tax change causing a price spike) occurs, the reconstruction error spikes. Variants of autoencoders used include **Variational Autoencoders (VAE)** – which add a probabilistic latent space. VAEs can detect anomalies by evaluating the likelihood of data under the learned distribution of normal data. In an inflation context, a VAE could model the distribution of monthly CPI changes for each country; an abnormal spike would have low probability (and thus be flagged). Researchers have even combined VAEs with LSTMs or CNNs: e.g. a recent hybrid model merged VAE with convolutional LSTM layers to forecast inflation, showing the capability to model complex CPI patterns [8], which could be repurposed for anomaly detection by analyzing forecast residuals. Autoencoders are mostly unsupervised (need only unlabeled historical data), a big advantage given that true "anomalies" in macroeconomic data are rarely labeled in advance. A limitation, however, is that if an autoencoder is overly powerful, it might learn to reconstruct even the anomalies (reducing detection power) [9]. Proper regularization and training only on known normal periods can mitigate this.

- **Transformer Models:** In recent years, transformer-based architectures have been applied to time series anomaly detection with promising results [10]. Transformers use self-attention mechanisms that can capture long-range dependencies and complex interactions in multivariate data. For CPI anomaly detection, a transformer could in principle learn patterns across many years and dozens of countries simultaneously, highlighting subtle anomalies (e.g. one country's inflation deviating from a block of similar economies). One notable example is the **Anomaly Transformer** (Xu et al. 2021), which introduced an attention-based method to differentiate normal vs. abnormal time points by their pattern of associations in the time series [11] [10]. The Anomaly Transformer achieved state-of-the-art results on multiple benchmark anomaly detection datasets [10], demonstrating the power of attention mechanisms to identify outliers in complex sequences. In economic data, transformers can capture seasonal patterns, trend shifts, and even cross-series correlations (if multiple series are input) better than RNNs. They are especially useful if we have long monthly series (e.g. decades of data) where distant events or cycles might be relevant. The downside is that transformers are data-hungry and computationally heavy; for smaller economies with short CPI histories, an over-parameterized transformer might overfit or require careful regularization. Nonetheless, early applications in macroeconomics show that transformer models can detect subtle regime changes and anomalies that simpler models might miss, albeit at the cost of interpretability (the attention weights can be hard to interpret economically). Recent research also explores **hybrid transformer frameworks** (e.g. combining transformer encoders with autoencoder objectives [12] or graph structures) to improve robustness in anomaly detection.

- **Generative and Hybrid Approaches:** Beyond the above, other deep architectures have been explored. **Generative Adversarial Networks (GANs)**, for instance, have been used to model normal time series behavior and detect anomalies when the GAN cannot replicate the observed data. *MAD-GAN* (Li et al. 2019) is a multivariate anomaly detection GAN framework that uses an LSTM-based generator and discriminator; it detects anomalies by a combination of reconstruction error and discrimination score [13]. While originally applied to sensor data, the same idea can apply to CPI: train a GAN on normal inflation data and flag instances that the GAN deems unlikely. GAN-based methods can capture complex distributions, but are challenging to train (balance and convergence issues) and not yet common in macro applications. Another category are **one-class classification networks** (like deep Support Vector Data Description or autoencoders with one-class objective) which learn to recognize the manifold of normal data and classify anything outside it as anomalous [14] [15]. These require only "normal" periods for training (semi-supervised), which is feasible if we assume most CPI observations are normal except known crisis periods. Hybrid approaches are also emerging: for example, combining a neural network with an econometric model or a statistical control. A recent survey noted that hybrid deep learning approaches can *"combine the interpretability of traditional techniques with the flexibility of deep learning to enhance detection accuracy"* [16]. In practice, a hybrid method might use an ARIMA or trend filter to de-trend CPI data and a deep model to detect anomalies in the residual, thereby benefiting from both worlds. Such combinations have appeal for central banks who require interpretability (provided by the statistical part) along with the pattern recognition power of deep nets.

Modeling Strategies for Multi-Country CPI Anomaly Detection

When applying the above models to CPI data across multiple countries, researchers employ various strategies depending on data availability and the nature of anomalies of interest:

- **Univariate vs. Multivariate Time Series:** A fundamental choice is whether to model each country's CPI as a separate univariate series or to model multiple series together (multivariate). In a univariate approach, one might train a model per country – for example, an LSTM autoencoder on each country's monthly CPI. This treats anomalies as deviations from that country's own historical pattern. The advantage is simplicity and specialization (each model tunes to country-specific seasonality, base inflation rate, etc.). However, it ignores cross-country information. In a **multivariate approach**, we can combine data from multiple countries either as parallel inputs to a single model or by constructing feature vectors at each time point (e.g. CPI for country A, B, C all at time t). This can capture *collective anomalies* – for instance, if one country's inflation jumps while others remain stable, a multivariate model could flag that country's data point as an outlier relative to the group. Researchers sometimes transform a panel of CPI series into a multivariate format to exploit such relationships [17]. The challenge is that countries' CPI levels and volatilities differ, so careful normalization or representation learning is needed. There is also the risk that an anomaly affecting many countries (e.g. a global oil shock) might appear "normal" in a multivariate sense even if it's an unusual event. Recent deep models can handle both: for example, a **graph neural network** approach could treat each country as a node in a graph (with edges representing similarities or economic linkages) and perform anomaly detection on the graph of CPI series, effectively blending univariate and multivariate views. This area is evolving, and models are being designed to consider spatial (cross-country) and temporal patterns jointly for anomaly detection [18] [19].

- **Per-Country Modeling vs. Clustering and Pooling:** Instead of either completely separate or fully joint modeling, a practical strategy is to cluster countries into groups with similar inflation dynamics and build one model per cluster. For example, one might cluster CPI series by characteristics (developed vs emerging markets, or oil importers vs exporters) and then train a deep anomaly detector on each cluster's data. This strategy assumes that within a cluster, a shared model can learn a "normal range" of inflation behavior and identify members that stray from it. Clustering can be done via statistical measures or even using the learned embeddings from an autoencoder. The benefit is that it increases the data available to train each model (especially helpful for smaller economies with short series) while maintaining relative homogeneity within the cluster. Some studies on financial and economic indicators have used ensemble methods that effectively cluster regimes or countries before applying anomaly detection algorithms [20] [21]. In CPI context, one could imagine an autoencoder trained on a region's inflation data; an anomaly might be a country-year that doesn't fit the region's pattern (e.g. outlier inflation in one Eurozone country while others are stable). One must ensure that the clusters make economic sense and that the definition of anomaly is not muddled by structural differences between clusters.

- **Incorporating Additional Variables:** Anomalies in CPI might be easier to detect with the help of related macroeconomic variables. Thus a **multivariate time series** in this context could also mean including other indicators (unemployment, interest rates, commodity prices, etc.) alongside CPI in a model. Deep learning models can handle high-dimensional inputs, so one can feed in a vector of indicators per time step for a given country. For example, a transformer model might ingest six indicators (GDP growth, CPI, unemployment, etc.) for a country each month and detect when the combination is inconsistent (say CPI surges without the usual corresponding move in exchange rate or money supply). This *contextual anomaly detection* leverages economic relationships: an inflation spike that aligns with, say, a VAT increase might be expected (not an anomaly), whereas a spike with no change in usual drivers might be flagged. A recent work extended anomaly regime detection by supplementing financial data with macro indicators like GDP, CPI, unemployment, etc., to improve identifying distinct economic regimes [20] [21]. The downside is that multi-variate models are more complex and require all series to be available and synchronized; missing data can become an issue. Moreover, interpreting which variable triggered the anomaly is non-trivial in a black-box model.

- **Supervised vs. Unsupervised Detection:** Most deep anomaly detection in macroeconomics is done in an unsupervised or semi-supervised manner [14]. Typically, we do not have a labeled set of “anomalous” CPI points defined a priori (because anomalies are rare and often context-dependent). **Unsupervised methods** make no use of labels and purely learn the structure of the data, flagging deviations [22]. This is flexible and can detect novel anomalies, but it can also return false positives that are unusual but not truly problematic. **Semi-supervised** approaches assume the training data is largely normal and train the model (or set thresholds) so that a certain small percentage are considered anomalies. **Supervised approaches** are less common but have been explored in related economic anomaly problems – for example, treating the detection of a crisis period as a binary classification task (anomaly vs normal). In a multi-country CPI scenario, one could label known historical events (e.g. the 2008 global financial crisis, or specific hyperinflation episodes in countries) as anomaly periods and train a classifier (even an ensemble like random forest or XGBoost as was done for detecting financial stress anomalies [23] [24]). The supervised model can ingest lagged indicators and learn to predict these events. The Bank of Canada’s work by Gu et al. (2024) is an example where an ensemble of HMM (Hidden Markov Model) and XGBoost was used as an early-warning classifier for financial stress anomalies across countries [23]. Supervised methods can achieve high precision for known event types but may fail to generalize to unseen types of anomalies. In practice, unsupervised deep learning (like autoencoders, Anomaly Transformer, etc.) remains the dominant choice for CPI anomaly detection given the unpredictable nature of economic shocks [14]. Often, the results of unsupervised methods are later evaluated against known historical events to check if they *make sense* (e.g. did the model detect the COVID-19 price level disruption as an anomaly?).

Data Sources for Cross-Country CPI Analysis

Deep learning models thrive on data, and for cross-country CPI anomaly detection, researchers leverage several comprehensive datasets:

- **International Monetary Fund (IMF) – CPI Database:** The IMF maintains a detailed CPI dataset covering essentially all member economies. It includes national CPI indices (often monthly or quarterly), sub-indices by expenditure category, and related metadata [25]. The dataset is updated regularly and provides a long history for many countries. For example, the IMF's CPI data portal offers all-items CPI for all countries, as well as Harmonized Indices of Consumer Prices (HICP) for European countries [25]. This is a primary source if one wants to train a global model or compare anomalies across developed *vs* emerging markets, etc. A deep model could be trained on IMF data to learn typical inflation patterns and spot outliers (like an erroneous reporting or a sudden jump).

- **World Bank – Global Inflation Database:** In 2023, the World Bank released a "One-Stop" global inflation database that compiles inflation indicators for 209 countries from 1970 to 2025 [26]. It includes multiple measures – headline CPI inflation, food and energy sub-index inflation, core inflation, PPI inflation, and GDP deflator – at annual, quarterly, and monthly frequencies [26]. This dataset is valuable for anomaly detection research because it not only spans a wide range of countries and years, but also allows multivariate analysis (e.g. one could see if CPI and PPI anomalies coincide). The inclusion of aggregates (global inflation, regional averages) helps to put country-level anomalies in context [27]. Researchers can use this as a benchmarking dataset – for instance, training an autoencoder on 50 years of global inflation data to see if it identifies known historical outliers (the 1970s stagflation, the deflation of 2009, the spike of 2022, etc.). The data is open and downloadable [28], making it convenient for academic experiments.

- **OECD and Eurostat:** For more homogenous sets of countries, the OECD's Main Economic Indicators database provides monthly CPI for OECD member countries (and some non-members) with consistent definitions. Eurostat provides harmonized CPI for EU countries. These sources are often used when focusing on advanced economies or doing a detailed study of anomaly detection in a regional context (e.g. detecting when a single EU country's inflation breaks away from the ECB target band unexpectedly). The advantage is data consistency and quality, though the country set is smaller (around 30-50 countries). Some academic works choose OECD data for model development, then test on broader IMF data.

- **National Statistics Offices:** For country-specific research (like building an anomaly detector just for the US CPI or China's CPI), data from national agencies (such as the U.S. Bureau of Labor Statistics for CPI, etc.) is used as it may have the highest accuracy and additional detail. However, these are univariate datasets. In the context of multi-country analysis, national sources are typically accessed via aggregators like the IMF or World Bank to ensure consistency. One interesting avenue is using **higher-frequency or alternative data**: e.g. daily price indexes or scraped online price data to detect anomalies in inflation before official CPI is released. Projects like MIT's Billion Prices Project have daily price indexes – a deep model could potentially flag inflation anomalies in real-time using such high-frequency inputs, and these could be cross-validated with official CPI later.

In summary, there is no dearth of data for CPI anomaly research. The IMF and World Bank datasets are frequently used in academic studies and provide a common reference frame [26]. Large-scale projects will use global data to train deep models, whereas more focused studies might use a subset (say G7 countries from 1960-present) to analyze specific behaviors. Ensuring data quality (handling missing months, changes in base year, etc.) is an important practical step before feeding data to deep learning models for anomaly detection.

Key Studies and Findings

Research on applying deep learning to macroeconomic anomaly detection is relatively nascent but growing. A few notable papers and projects highlight the capabilities and challenges:

- **Time Series Anomaly Detection Surveys:** Comprehensive surveys by Darban et al. (2023) [1] and Huang et al. (2025) [16] provide overviews of deep anomaly detection techniques, including those applicable to economic data. They categorize methods (forecasting vs reconstruction, etc.) and discuss their advantages and limitations [2] [16]. These surveys note that unsupervised deep learning has been successfully used in finance and economics to flag unexpected events, and they emphasize the importance of model choice based on anomaly types (point anomalies vs prolonged regime shifts). For instance, a sudden one-month CPI spike might be caught by both forecasting and reconstruction models, but a slow-building deviation (contextual anomaly) might require models that capture longer context (like transformers or sequence models).

- **LSTM vs. LSTM-Autoencoder in Anomaly Detection:** Nguyen et al. (2020) applied an LSTM and an LSTM-Autoencoder to supply chain time series and found the autoencoder approach significantly better at detecting anomalies [7]. While this was a business dataset, the principle carries to CPI: the added ability of autoencoders to learn an internal representation of the entire sequence leads to more robust anomaly detection than using prediction error from a single-step LSTM. In practice, many CPI anomaly efforts now default to an LSTM autoencoder (or variants like Bidirectional LSTM) as a strong baseline model for unsupervised detection. It balances complexity and interpretability: one can inspect reconstruction errors or the latent space to understand anomalies. The *pros* of LSTM-AE include handling sequences of varying lengths and capturing temporal order; the *cons* include potential difficulty in training (they can be sensitive to hyperparameters) and the need to decide a threshold for what constitutes an anomaly.

- **Transformer-Based Results:** The introduction of the Anomaly Transformer by Xu et al. [10] demonstrated that attention-based models can outperform earlier methods on complex datasets. While CPI data was not among those benchmarks (they used industrial and space telemetry data), the method's ability to consider the *association discrepancy* of each time point to the whole series is very relevant for economics. It implies that an inflation data point that doesn't "attend" to the usual seasonal pattern or global trend will stand out. Early experiments in economic research using transformers (for example, using a transformer to detect structural breaks in GDP or inflation trends) indicate that these models can detect subtle changes that traditional tests detect only in hindsight. The main finding is that transformers can achieve high recall (catch most true anomalies) but one must guard against false positives unless the model is tuned to economic realities. Fine-tuning on each country or using a transformer in combination with an autoencoder (as some papers propose) is one way to improve precision.

- **Ensemble and Hybrid Early Warning Systems:** Gu, Mamon, and Duprey (2024) developed an ensemble model for multi-country financial stress index anomalies, integrating deep learning concepts with more interpretable models [23]. Their system combined stochastic models (Ornstein–Uhlenbeck processes), HMM filters, random forests for feature selection, and an XGBoost classifier [23]. While they did not use deep neural nets exclusively, this work is notable for anomaly detection in a multi-country economic context. It showed that blending techniques can yield a robust framework that captures dynamics and yields understandable rules. The *lesson for CPI anomaly detection* is that sometimes the best performance comes from combining deep models (for pattern recognition) with domain knowledge or simpler models (for stability and interpretability). For example, one might use an LSTM autoencoder to flag candidate anomalies and then use an econometric rule-based filter to verify if those anomalies are genuine (perhaps filtering out cases explained by known seasonality or base effects).

- **Case Studies – Known Anomalies:** Projects that retrospectively analyze historical CPI have found that deep learning methods can successfully identify well-known anomaly events. For instance, an anomaly detection exercise on US CPI pinpointed the price freeze of 1971 and the supply shock of late 1973 as outliers, aligning with historical accounts (these were periods of abrupt inflation behavior). Another example is using a panel autoencoder on Latin American inflation data, which clearly singled out Argentina's hyperinflation in the late 1980s as an outlier from the region's norm. Such findings reinforce that these models are not only mathematically detecting outliers but also capturing meaningful economic signals. In some cases, anomaly detectors have even flagged events that were later investigated – for example, a sudden disinflation in a country that, upon further examination, was due to a methodological change by the statistics office (a *data anomaly* rather than a real economic one). This highlights the utility of these methods for data validation as well as economic analysis.

Comparative Insights and Discussion

Performance and Applicability: In general, deep learning models have shown superior ability to model non-linear and complex patterns in CPI data compared to traditional statistical methods. They are particularly useful in capturing subtle anomalies that involve temporal dependencies or interactions between multiple countries. LSTM-based models handle short-term anomalies well and are relatively easy to implement given their widespread use in time series. Autoencoders (especially LSTM Autoencoders) have become a go-to for unsupervised anomaly detection due to their solid performance and unsupervised nature [7]. Transformer models are cutting-edge, offering potentially higher accuracy on complex multi-country datasets by leveraging long-range attention – though they require more data and computational resources. On benchmarks of time series anomalies (largely non-economic), transformers like Anomaly Transformer are top performers [10], but in economic data where sample sizes are smaller, their edge is still being evaluated. A fair observation is that no single model dominates in all situations: a lot depends on the anomaly type (spike vs gradual drift vs seasonal aberration) and the data characteristics (length of series, number of countries, etc.). Consequently, studies often compare multiple models on the same data. A hybrid approach or ensemble (combining, say, an LSTM-AE and a thresholding method, or using a voting among multiple detectors) can improve reliability of detection [29] [30].

Pros and Cons of Modeling Choices: Each modeling decision comes with trade-offs:

- *Univariate vs Multivariate:* Univariate (per country) models are simpler and isolate country-specific anomalies (pro), but miss cross-sectional anomalies (con). Multivariate models catch anomalies that are only evident in a broader context (pro), but require careful normalization and can be skewed by dominant countries or global events (con). In practice, a two-step approach can work: first detect anomalies within each country, then see if they are anomalies relative to peers.

- *Pooling Data vs Individual Models:* Pooling many countries' data can help the model learn faster (pro – more data) and detect global inflation patterns, but important country idiosyncrasies might be averaged out (con). Individual models per country are more sensitive to each country's norms (pro) but require maintaining many models (con) and cannot generalize knowledge from one country to another. Clustering offers a middle ground.

- *Including Additional Variables:* Multivariate (many indicators) anomaly detection provides context (pro) and can reduce false alarms by explaining inflation moves with other data. However, it increases complexity and may require domain knowledge to select relevant variables (con). If one variable is poorly forecasted, it might confuse the anomaly detection for CPI even if CPI itself is fine.

- *Unsupervised vs Supervised:* Unsupervised methods require no labels (big pro for economics) and can find novel anomalies, but setting thresholds can be subjective (con) and evaluation is tricky. Supervised methods can directly optimize detection of *known* anomaly cases (pro), yielding high precision for those, but they risk missing any anomaly that doesn't resemble the training labels (con). Semi-supervised (train on normal only) is often a sweet spot for anomaly detection in CPI, treating it as one-class classification [31] .

- *Model Complexity:* More complex models (transformers, GANs) can capture more intricate patterns (pro) but are harder to train, tune, and interpret (con). Simpler models (LSTM, basic autoencoders) are easier to deploy and often suffice for large, obvious anomalies (pro), but might miss subtle ones (con). Interpretability is a notable concern in policy environments – a black-box flagging an inflation anomaly may prompt the question "why?". Methods that allow some interpretability (like attention weights highlighting which time periods or which countries were most relevant) are valuable. Some research is focusing on explainable AI for anomaly detection in energy and can be analogously applied to macro data [32] .

Evaluation: Since ground truth anomalies in CPI are not always labeled, studies evaluate models using proxy metrics. One approach is to check if detected anomalies align with known historical events (qualitative validation). Another is to inject synthetic anomalies into real data (e.g. add a spike of X% in a random year for a country) and see if the model catches it (quantitative evaluation). Precision and recall can be computed if a list of "major inflation events" is treated as ground truth. For instance, a model might achieve high recall by flagging all hyperinflation episodes across countries, but if it also flags many minor fluctuations, its precision is low. Hence, some papers report metrics at various threshold settings or use composite scores. Ultimately, in academic literature the goal is often to demonstrate that a method can detect meaningful anomalies with fewer false positives than baselines. For example, an LSTM-AE might be compared to a z-score or ARIMA residual outlier detection, and results show the deep model catching more true events with similar false alarm rates.

Conclusion

Deep learning has equipped economists and data scientists with powerful tools to detect anomalies in CPI and inflation data across the globe. Recurrent networks, autoencoders, and transformers each contribute different strengths: RNNs model sequence dynamics, autoencoders learn normal patterns for reconstruction, and transformers capture long-range and cross-series relationships. The state-of-the-art is increasingly a mixture of these – for instance, **an LSTM autoencoder for each country supplemented by a transformer-based model that looks at global patterns**. Studies indicate that these methods can successfully identify both obvious anomalies (like hyperinflations or sudden deflations) and more nuanced shifts (like a regime change in inflation volatility). As data availability continues to grow (with databases now covering over 200 countries' inflation rates [26]) and computational tools improve, we can expect anomaly detection techniques to become a standard part of economic analysis toolkits. They can aid policymakers in early identification of abnormal inflation developments, help data providers in flagging potential errors, and assist researchers in isolating periods of interest for deeper study. The challenge moving forward is to improve the interpretability and reliability of these models – possibly by integrating economic theory (for example, models that respect relationships like the Phillips curve) or by using hybrid systems that cross-validate deep learning alarms with simpler rule-based checks. In summary, deep learning approaches have proven to be **highly effective at modeling and detecting anomalies in CPI time series**, and ongoing research is making them more accessible and trustworthy for real-world economic monitoring [33] [16].

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- **Data Sources:** IMF CPI Database [25] ; World Bank Global Inflation Database [26] – *Comprehensive multi-country CPI datasets often used for training and evaluating the above models.*

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