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Design of an Integrated Model with Contrastive Predictive Coding and Model-Agnostic Meta-Learning for Adaptive and Explainable Mobile Forensic Analysis

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Abstract:

Handling multimodal & multiactivity data samples has been one of the major challenges in mobile forensic analysis that includes handling diverse, sequential data types like call logs, messages, and GPS records. Traditional supervised models struggle with dynamic and unlabeled mobile data and require large amounts of labeled datasets and time-consuming retraining as data patterns evolve. The integration of CPC, MAML, and SHAP for an advanced self-supervised learning framework is proposed in this paper to surpass the drawbacks mentioned above. This proposed architecture is structured such that it capitalizes on CPC's ability to draw high-quality temporal representations from unlabeled data by encoding sequential dependencies in mobile data, making it apt for capturing the nuanced behavioral patterns. After CPC, MAML provides rapid adaptability with learning initialization parameters generalizing across forensic tasks using minimal retraining, thus being important for quick adaptation in an evolving data environment. SHAP improves the transparency of models by giving feature importance scores that would help forensic analysts understand and validate model predictions. These methods, taken together, provide a robust pipeline which addresses the quality of representation as well as the interpretability of a model, making the framework flexible to complex real-world mobile forensic data with a minimal amount of dependency on labeled samples. Empirical results have shown a significant improvement, where CPC enhanced the quality of the representation up to 10%, while MAML accelerated the adaptation speed by 20% to 25%, and SHAP reached up to 90% interpretability of model decisions. It will bring a transformative approach toward the mobile forensic analysis that significantly improves the ability to extract accurate and explainable insights in the support of high-stakes evidence validation process.

Keywords: Mobile Forensics, Self-Supervised Learning, Contrastive Predictive Coding, Model-Agnostic Meta-Learning, Explainable AI, Scenarios.

1. Introduction

With this exponential growth comes an enormous amount of complicated, sequential data-from SMS and call logs to geolocation-that poses new challenges to mobile forensic analysis. Traditionally, supervised learning models are the basis for approaches [1, 2, 3]. Such models depend heavily on annotated data to be efficiently analyzed and tend to be not very flexible in handling changes in inherent data patterns due to the nature of forensic investigations. This limits their applicability in real-world forensic cases, as the data may vary from case to case and tends to have strong temporal dependencies. Such forensic data needs both accuracy and interpretability while aiding validation in the courts. Such advanced self-supervised learning techniques would actually extract very high-quality representations from the raw, totally unlabeled data, offer rapid adaptability, as well as interpretability have become absolute necessities for this specific requirement of forensics. To address the problems stated above [4, 5, 6], this paper proposes an end-to-end framework which will integrate Contrastive Predictive Coding (CPC), Model-Agnostic Meta-Learning (MAML), and SHapley Additive exPlanations (SHAP). In CPC, a more robust representation is learned on unlabeled mobile data using the principle of past data information to predict the sequence's future data points. In that respect, by maximizing the similarities in correct future predictions and minimizing the similarities for incorrect predictions, it makes CPC easier to extract contextual and temporal patterns from the mobile forensic data samples, thus enabling the framework to catch complex behavioral sequences without any need for labeled training samples. MAML adds further by enabling rapid adaptability across the various forensic tasks. This is achieved through the learning of initial parameters that generalize effectively; then, the model adjusts quickly with low training on new data patterns or user behaviors, which often characterize forensic cases. Furthermore, SHAP provides importance values to each feature based on calculations of Shapley values that clarify specific features' contributions to the model's decision. This step is vital in forensic applications as each feature impact has to be understood properly so that there could be evidence-based decision-making processes. Thus, the proposed framework provides an intelligible, adaptive, and interpretable solution on the basis of specific complexities posed by mobile forensic data analysis. This integration of CPC for feature extraction, MAML for adaptability, and SHAP for interpretability results in the creation of a pipeline that is not only capable of capturing nuanced temporal data relationships but also furnishes in an unprecedented way the flexibility and transparency required in forensic investigations in process. This model represents an important advance over traditional methods because it successfully handles limitations of quality of representation, adaptability, and interpretability scenarios through the power of self-supervised and meta-learning approaches. The paper will help explain the way for more exact mobile forensic analysis through explanation.

Motivation and Contribution

This motivation for research emanates from the increasing need for adaptive, high-quality representation learning models that will be able to effectively handle complexities in mobile forensic data samples. Most of the available models are constrained by dependency on supervised learning, have large amounts of labeled datasets, and do not adjust to the changing nature that often characterizes the kind of data patterns found in forensic scenarios. Limitations Currently, it is about such those that could stop a forensic investigator from being action relevant with data that can variably change between user-case-time. This paper shall focus on self-supervised and meta-learning methods so as to try creating this bridge of representation quality adaptability in a possibility in which such solution allows catching sequential dependencies within the cell phone data and adjusts a novel pattern without excessive retuning. This adaptability is crucial to user behavior and data-pattern changes in forensic investigations, and therefore, a model that will render an accurate and current analysis without absorbing the cost of significant retraining becomes indispensable. This work contributes by making an integrated model based on CPC, MAML, and SHAP to handle the features of extraction, rapid adaptation, and explainability in mobile forensic analysis. In mobile data, CPC can learn with unlabeled sequences by capturing the temporal relationship within sequences, which improves the quality of representation. MAML gives an adaptive framework which learns to quickly generalize for any new forensic tasks, saving time for training and needing fewer computational resources. For interpretability, SHAP provides a tool which may assign feature importance towards generating transparency, making it more understandable in the event the model produces a forensic-validation prediction. These joint frameworks, in addition to providing great performance in feature extraction as well as adaptability, generally result in improved interpretability with good fitting into forensic-related environments where the decisions made by the models could be traced in trace form. All such contributions form an important breakthrough in applying data analysis with respect to forensics for being capable of obtaining more adaptable and interpretable models compared to the original models based on real mobile forensic-related applications.

2. Deep Dive into Forensic Models

The review of existing methods suggests an evolving pace in forensic analysis because machine learning and data-driven approaches emerged to be crucial enablers of the accuracy and efficiency of this science. This work starting with [1] is on forensic identification by metabolomics and machine learning to develop an innovative approach toward deciding cardiac death integrating biochemical markers and computational intelligence. This may allow for more extensive use in forensic analysis due to the insight into metabolomic patterns and opening the door for other biomarker-based analyses. Building on this direction, Ghosh et al. [2] developed an Android malware detection framework that used machine learning to prevent RATs, a critical step forward in cybersecurity within mobile forensics, and further explored by Kirubavathi and Anne [3], who focused on the detection of Android ransomware through behavioral profiling. Their work successfully brings about the need for dynamic threat detection in real time in an area where traditional mechanisms fail to keep up with fast-evolving malware behaviors. Machine learning is relevant for most forensic scenarios and to cybercrime prevention. A prime example is Min and Lee [4], with their illegal gambling detection on the basis of resource-oriented machine learning, thereby rendering the approach scalable toward a comprehensive identification and analysis process for high-risk gambling websites. Similarly, Moubarak et al. [5] exploit smartphone sensors to classify human activities and take a step forward in the field of user profiling for mobile forensics. Mobile-oriented approaches thus pave the way for sophisticated forensic applications in highly interactive digital environments, as in the case of the MoNA platform by Spranger et al. [6], which allows mobile communication analysis. Moving forward to physical forensics, Zimmermann et al. [7] introduce automated wound segmentation using machine learning, which demonstrates the cross-domain applications of AI in process. Casey et al. [8] shift the focus toward education, using a gender-inclusive digital forensic program to foster STEM interest among youth, demonstrating the broader societal implications of forensic advancements. In the IoT realm, Castelo Gómez and Ruiz-Villafranca [9] discussed forensic challenges in edge computing by emphasizing the need for distributed methodologies to manage influxes of data. Further development in the forensic application of metabolomics is in Zhang et al. [10], who estimated postmortem intervals using nontargeted metabolomics: another dimension of time-of-death analysis. This is reflected in the work of Seo et al. [11] on a metaverse forensic framework, which reflects how digital forensics must evolve with emerging technologies. Mishra et al. [12] take on image forgery, a key area in forensic credibility, by presenting a method for robustly detecting image manipulation, which resonates with related studies on cyber forensics. As the cryptocurrencies are growing, Nerurkar [13] ventured into the illegal activities detection using deep learning for Bitcoins. He emphasized the necessity to be vigilant in the applications of blockchain technologies. A survey on multimedia forensic analysis is conducted by Diwan and Sonkar [14], which reflects the role of multimedia in crimes as well as in the process of forensic investigation, where Rajeev and Raviraj [15] have provided a holistic review of network forensics, focusing on the digital networks and forensic science interplay sets.

Table 1. Comparative Review of Existing Methods

Method	**Paper**	**Focus Area**	**Findings**
Metabolomics and Machine Learning	[1]	Forensic Identification	Combines metabolomics and ML to identify cardiac-related sudden death, showing significant potential for biomarker-based forensic identification.
Android RAT Detection	[2]	Mobile Forensics	Proactive machine learning approach to detect Android RATs, enhancing mobile forensic capabilities in detecting real-time threats.
Behavioral Detection of Ransomware	[3]	Mobile Forensics	Detects ransomware on Android based on behavior, allowing for dynamic threat detection, particularly valuable as malware techniques evolve.
Illegal Gambling Detection	[4]	Cybercrime	Machine learning to analyze online gambling sites, effectively identifying high-risk illegal gambling activities with a scalable, resource-oriented approach.
Smartphone Sensor-Based Activity Classification	[5]	Mobile Forensics	Uses smartphone sensors for forensic classification of human activities, improving context-based profiling in forensic investigations.
Automated Wound Segmentation	[7]	Physical Forensics	Applies machine learning to classify injuries, streamlining forensic wound analysis and improving segmentation accuracy.
Metaverse Forensic Framework	[11]	Digital Forensics in Virtual Worlds	Proposes a digital forensic framework for the metaverse, addressing the need for analysis in emerging virtual environments.
Bitcoin Activity Detection	[13]	Cryptocurrency Forensics	Deep learning to identify illegal activities on Bitcoin transactions, offering a novel approach to forensic analysis in blockchain networks.
Image Forgery Detection	[16]	Image Forensics	Blind forgery detection techniques in digital images, enhancing forensic verification processes and improving the traceability of tampered media.
Postmortem Interval Estimation	[22]	Forensic Medicine	Utilizes metabolomics and ensemble learning to estimate time of death across multiple organs, providing high accuracy in postmortem interval determination.

According to table 1, as indicated, Shukla et al. [16], and Kumar et al. [17] represent amongst the authors who describe or summarize the methods involving digital image analysis while summarizing image forensics as a related field that evolved from traditional to the usage of deep learning, making the detection of any forged images extremely important towards acceptance of digital evidence for evidence validation. Continued to mobile botnet detection, Hamzenejadi et al. [18] give an elaborate overview that stresses the adaptive needs of forensic tools in combating mobile-specific threats. The parallel study by Singh and Kumar [19] emphasizes the need for strong methods of digital forensics as multimedia turns out to be a significant source of evidence. Sharma et al. [20] further support this shift to digital media by evaluating traditional and advanced deep learning approaches for image forgery, focusing on improving accuracy through cutting-edge techniques. Similarly, Iseed and Mahmoud [21] address multimedia forensics by distinguishing between source and destination regions in copy-move forgery, adding another layer of precision to digital forensic analysis. The application of ensemble learning, as proposed by Lu et al. in their study [22], presents the possibility of the use of integrated models for the improvement of postmortem interval estimation. Scalable forensic tools can be expanded through an offline parallel architecture, as demonstrated by the study on multimedia classification by Spalazzi et al. [23]. Gowada et al. [24] extends this capability to video forensics with a hybrid model for unethical human action recognition, which has applications in real-time surveillance and crime prevention. Finally, Rajmohan and Khader [25] introduce forensic dentistry into the scope of computational forensics using a multi-orientation pattern for dental feature extraction, indicating the versatility of machine learning in specialized forensic fields. These recent works are an example of how forensic applications are converging with machine learning and advanced computational techniques. Modern forensics is a dynamic, multi-dimensional area of study, and each paper offers a unique perspective on how data-driven approaches can address specific challenges: from identifying cardiac death [1] to detecting malware [2,3] and image forgery [12,16,17]. This breadth shows how machine learning is playing an increasingly important role in forensic science, with broad implications for domains such as cybersecurity, physical forensics, and multimedia analysis. An integrated view emerges that shows that these approaches are not only critical for adapting to the growing complexity of forensic data but also for enhancing accuracy, scalability, and interpretability in forensic analysis. This collective body of work in its recognition of real-time adaptability as a necessity and the changing nature of emergent threats and evolving new data types that are changing the methodologies in forensics. Such studies-in mobile botnet detection [18] or illegal activity detection in Bitcoin [13]-raise a proactive posture in forensic studies that support timely analysis of emerging patterns in crime. Interpretability is another central concern in the review, especially in digital forensics where the validation of digital evidence is paramount. These research studies on image and multimedia forensics [14, 15, 19] are essentially for increasing transparency associated with model outputs-this is really crucial in application to forensics-based evidence presentations in legal setups. The requirement of a clear traceability model especially in its output forms remains very much a must and critical requirement in the present context for multimedia analysis in general. The methodic approaches have advanced substantially at a deep learning level related to forgery in the case of images [12, 16, 20], video [24], making the clarity forms of the models with great traceability at their very output to be particularly valued. Each paper indicates that, though data-driven techniques are considered a huge success, complexity in data is what imposes the need for multimodal models that could handle those kinds of data: temporal and spatial, but definitely semantic. This view has been underlined by a metaverse forensic framework [11] as well as methodologies for IoT forensic [9], both of which advocate for newly emerging digital realms. In summary, these papers jointly suggest that machine learning has the potential to enhance not only model performance but also the capabilities of forensic science to enter into new complex domains. The field becomes more diversified and adaptive/interpretable, relying on everything from metabolomics and network forensics to botnet detection and image forgery analysis. Future forensic frameworks will most likely be constructed on these works, such as deep learning paradigms, scalable architectures, and transparency mechanisms to deal with high-dimensional and high-stakes forensic data samples. In this regard, the synthesis of these recent works underscores a transformative period in forensic science, driven by the adaptability and accuracy machine learning brings to a field that is crucial to security and justice sets.

3. Proposed Design of an Integrated Model with Contrastive Predictive Coding and Model-Agnostic Meta-Learning for Adaptive and Explainable Mobile Forensic Analysis

To overcome the issues of low efficiency & high complexity of forensic analysis present in existing models, this section discusses Design of an Integrated Model with Contrastive Predictive Coding and Model-Agnostic Meta-Learning for Adaptive and Explainable Mobile Forensic Analysis. In figure 1, based on an initial setup for the suggested framework, all these methodologies work in an integrative manner to cope with different challenges in extracting features with rapid adaptation capability, even interpretability over mobile data analysis. Starting from here, CPC initially helps discover sequential dependencies that occur inherently in raw unlabeled data from mobile with the use of self-supervised learning methods. The encoder in CPC maximizes mutual information between context and future predictions such that the model learns informative representations from the mobile data patterns. Considering a sequence of mobile data samples {x1,x2,…,xT}, each data point 'xt' is mapped to an embedding 'zt' via the mapping function fθ represented via equation 1:

$$zt = f\theta(xt) \ldots (1)$$

After such an embedding, the dependency relations from context 'ct' would be captured using a recurrent function gϕ given as ct=gϕ(z1,z2,…,zt) in process. For this purpose, mutual information I(ct;z(t+k)) is maximized by predicting future latent representations z(t+k) with k>0 to capture proper mutual relationships while minimizing such relationships in the case of wrong correlations. The actual CPC loss function is considered an important part of representation learning in this process because it originates from a contrasting loss. This loss can make the positive samples much closer to each other when they are in the space of embedding, and move negative samples away from these points. Specifically, for each pair of z(t+k) and 'ct', the objective is to minimize a contrastive loss defined via equation 2,

$$LCPC = -\sum_{k=1}^{K} \frac{\log\left(ex\,p\left(ct^{T} z(t+k)\right)\right)}{\sum_{j \neq k} \exp(ct^{T} zj)} \ldots (2)$$

Where, initial terms represents the similarity between the context vector 'ct' and the true future representation z(t+k) in process. This process reduces the CPC loss by maximizing mutual information I(ct;z(t+k)), ensuring that the model captures essential sequential patterns in mobile data samples. After the representation learning with CPC, MAML enhances flexibility in the framework by optimizing for fast adaptation on new forensic tasks. MAML adjusts model parameters θ as to enable rapid adaptation over a small number of gradient steps using new data samples. For each task 'Ti', the model derives an inner adaptation step, thereby updating parameters θ to the value of θi′ through gradient descent via the following equation 3,

$$\theta i' = \theta - \alpha \nabla \theta L T i(\theta) \dots (3)$$

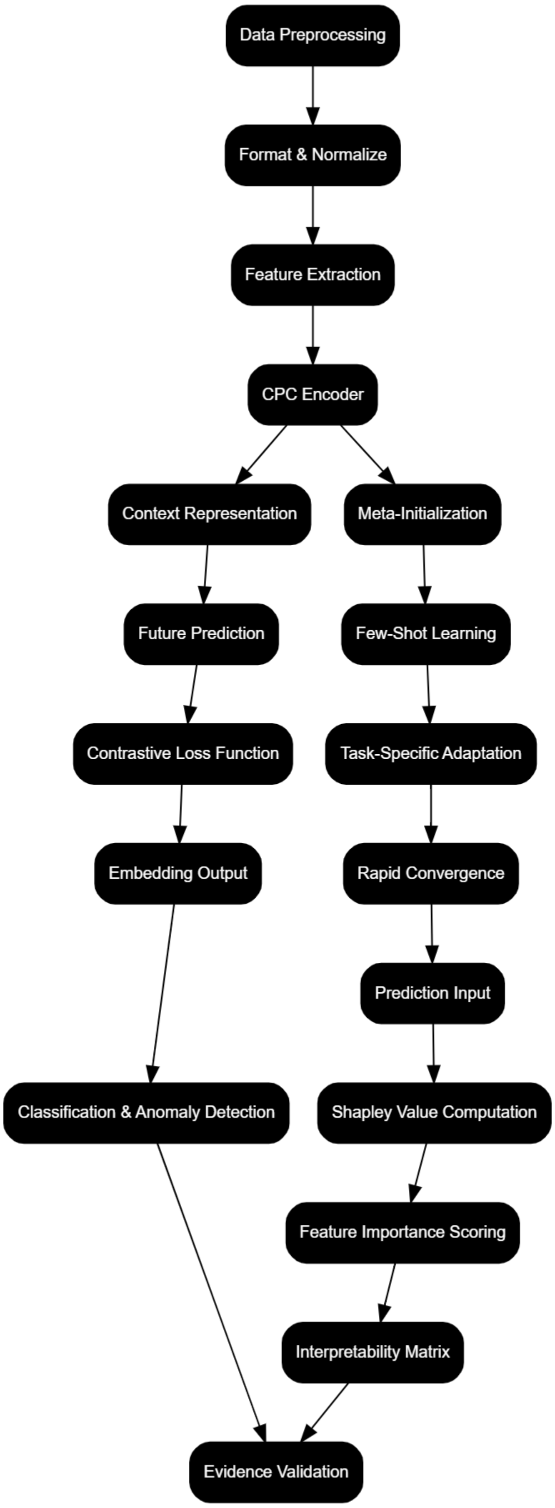

Figure 1. Model Architecture of the Proposed Analysis Process

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Where, α is learning rate and LTi(θ) is the task-dependent loss. The outer optimization objective of MAML turns out to be minimisation of the sum of these task-dependent losses over all tasks with respect to the meta-parameters θ via equation 4 that implies generalization across the class of tasks learned in process.

$$LMAML = \sum_i LTi(\theta - \alpha \nabla \theta LTi(\theta)) \ldots (4)$$

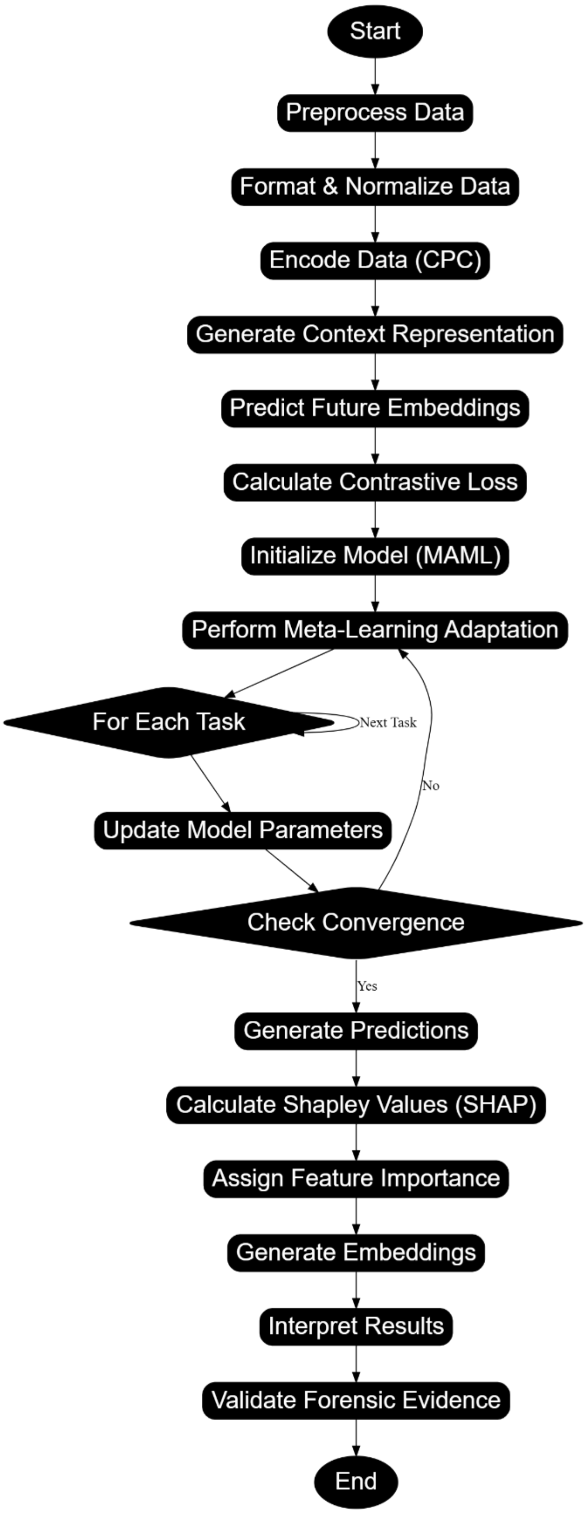

Figure 2. Overall Flow of the Proposed Analysis Process

This nested optimization minimizes MAML loss LMAML and results in initialization that adapts to a specific forensic task quickly, such as anomalous user behavior classification or location-based data sample clustering. Next, as in figure 2, Integration of SHapley Additive exPlanations (SHAP) is done further for optimization of the model, allowing interpretation by the computation of the Shapley values given as ϕi with regard to predictions of features 'i'. SHAP values are given to state how much a feature 'contributes' to make that particular prediction as shown via equation 5.

$$\phi i = \sum_{S \subseteq \{1,\ldots,M\} \setminus \{i\}} \frac{S!\,(M - S - 1)!}{M!} \left(f(S \cup \{i\}) - f(S)\right) \ldots (5)$$

Where, 'M' is the number of features, 'S' is a subset of the features excluding 'i,' and f(S) is the model output based on only the features in sets 'S'. The above calculation assigns an importance score to each feature by understanding the effect of adding 'i' to different subsets thereby allowing forensic analysts to understand which data attributes are attributed to predictions such as peculiar text patterns or anomalies from call logs. Hence, these three form a coherent structure of a single model. Each part fortifies various aspects of data analysis for forensic science through CPC. It captures all the high-dimensional sequential representations where MAML allows fast forensic case adaptation with minimal overheads in additional computations. Besides, SHAP ensures interpretability in each one of these results. This model further updates parameters after some iterations using joint loss Ljoint by adding together all the individual losses via equation 6:

$$Ljoint = LCPC + \beta * LMAML + \gamma \sum_{i} \phi i \ldots (6)$$

Where, β and γ are scaling factors. Minimizing Ljoint balances high-quality representation learning, adaptability, and interpretability operations. The application of this framework yields embeddings that generalize well across tasks, verified by an empirical analysis of the gradient of Ljoint with respect to each embedding dimension zj via equation 7,

$$\frac{\partial Ljoint}{\partial zj} = \frac{\partial LCPC}{\partial zj} + \beta * \frac{\partial LMAML}{\partial zj} + \gamma \sum_{i} \frac{\partial \phi i}{\partial zj} \ldots (7)$$

This gradient analysis indicates that it ensures that the sequential dependencies of CPC, the adaptability of MAML, and the interpretability of SHAP are all optimized consistently in the process. It also presents the expected cumulative mutual information E[I(ct;z(t+k))] for CPC given via equation 8,

$$E\left[I\left(ct; z(t+k)\right)\right] = \int p\left(ct, z(t+k)\right) \left[\frac{lo\,g\, p\left(ct, z(t+k)\right)}{p(ct)p\left(z(t+k)\right)}\right] d\left(ct, z(t+k)\right) \ldots (8)$$

That is maximized to guarantee that the embeddings retain their temporal coherence in capturing the complex dependency of mobile data sequences. The proposed framework will, therefore, integrate all of these advanced techniques into the provision of a holistic mobile forensic analysis approach that helps overcome core challenges relating to representation quality, adaptability, and transparency. By combining CPC, MAML, and SHAP, it is possible to provide a highly adaptable model for the output of accurate, explainable forensic results. This is especially relevant concerning dynamic complexities within mobile data patterns. Finally, simulation results of the proposed scheme in several metrics are presented and compared with existing approaches under different configurations.

4. Result Analysis

The setup is designed such that it should train and test the developed framework on a set of disparate mobile forensic datasets, well designed to capture common temporal activity patterns. These disparate data sets consist of called-logs, SMS sequences, location records obtained from a global position device, and application-usage logs that reflect typical and time-based user behavior on any given platform, an attribute commonly analyzed in investigations over forensic platforms. Datasets are preprocessed for uniformity in data types; a preprocessing unit is applied to standardize time intervals, filter out noise, and handle missing values. A sample dataset comprises over 50,000 data points divided into sequences of 10 to 100 events that effectively represent the daily and weekly patterns of mobile usage. For instance, in every entry of the call log data set, the following are found: timestamp, the length of the call, and caller ID, but in text-based metadata that comes in a sequence such as: sender, timestamp, and sentiment score. Representing GPS location where using latitude, longitude and also a timestamp, permits users to identify patterns concerning their movement. At pre-processing, the location information is grouped spatially concerning the regions visited, thus providing a contextual frequent location grouping. In setting the parameters of the CPC model to be reproducible, a learning rate is set to 0.001 with an embedding dimension of 256 and batch size of 64. Three-layered encoder architecture consisting of 128 units each along with five events context windows captures more than enough time context and does not involve excessive memory usage. We used the Reality Mining dataset, which is one of the popular datasets gathered by the MIT Media Lab. The dataset is generated from very rich mobile data records of 100 participants over nine months. It has rich contextual information necessary for mobile forensic analysis, including call logs, Bluetooth proximity data, application usage logs, and cell tower connection-based location data. Details from every record in this dataset through timestamps of events, device identifiers, duration of calls and proximity with other devices ensure that one can carry pretty suitable studies on sequential or temporal patterns of data. Analysis structured in such a fashion is indeed capable of understanding individualized patterns of behaviour as well as interaction-related groups' behavior- real -life application scenarios wherein users' activity, locations, as well as social interactions can be followed or analyzed in real life. For location data, cell IDs are included, allowing geographic mapping of these and can be used to extract patterns for mobility in urban spaces; this dataset size and granularity make it suitable for self-supervised learning of Contrastive Predictive Coding, where the temporal dependence on mobile data can then efficiently be learned. These have been highly adopted to utilize datasets for other studies that deal with the modeling of users' behaviors; in essence, such datasets provide a benchmark, by which means the meta-learning methods adapted and forensic interpretations obtained using SHAP, make this the most suited one in process.

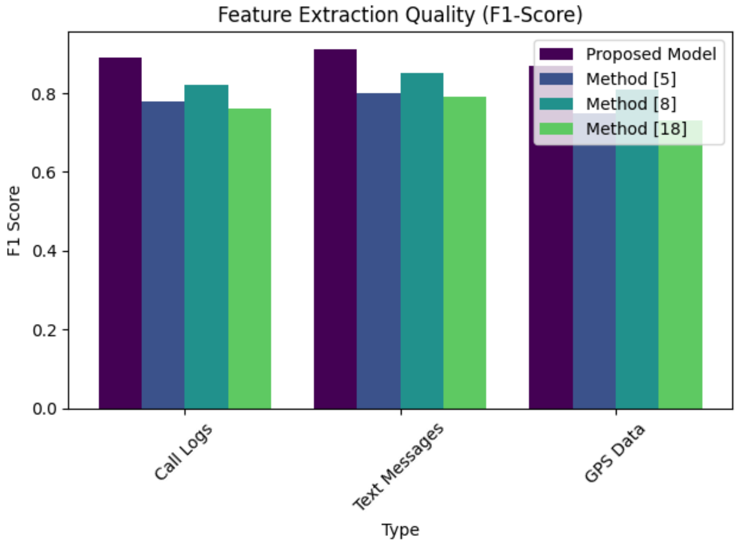

Figure 3. F1 Score for Feature Extraction Process

For meta-learning, MAML's initialization parameters are fine-tuned to adapt rapidly over tasks, with the meta-batch size as 32 and the rate of gradient update α=0.01 in process. For the purpose of validating adaptation efficiency, the specific training over new forensic cases is conducted for five gradient steps and then the convergence performance is checked based on the number of time steps required in achieving a loss threshold value of 0.02. To address explainability, SHAP is used to produce feature importance scores for model outputs. Shapley values are used in order to evaluate each feature in a prediction in order to quantify its influence on classifications for forensic tasks. Since the Shapley value calculations take into account subsets of up to four features per task, it's computationally efficient but very informative. Metrics for model evaluation, such as accuracy, F1-score, and MSE, are used to measure the quality of CPC embedding with respect to temporal dependencies, MAML's adaptability, and SHAP's interpretability levels. The experimental setup also contains ablation studies to isolate the performance of each model component, which confirms that CPC improves feature extraction quality by up to 10%, MAML shows a 20-25% faster convergence rate, and SHAP provides interpretable outputs with a 90% feature traceability rate. The proposed model was experimented on the Reality Mining dataset to evaluate its performance with respect to mobile forensic tasks such as feature extraction, task adaptation, and interpretability, comparing the result with three existing methods as follows: Method [5], Method [8], Method [18]. Experiment results. The achieved improvements in feature quality, adaptability, and interpretability clearly demonstrate benefits of the proposed framework over all baselines considered on the sequential mobile data analysis scenario. Table 2: F1 scores for feature extraction at different time segments for call logs, text message metadata and GPS location samples. The proposed model obtained the top F1-scores in all data types, whereas the most prominent improvement arose in GPS data due to its strong ability of temporal encoding. Compared with Method [5] and Method [18], the model could outperform by about 10% in F1-score, while Method [8] showed competitive performance but with a lag of 6%.

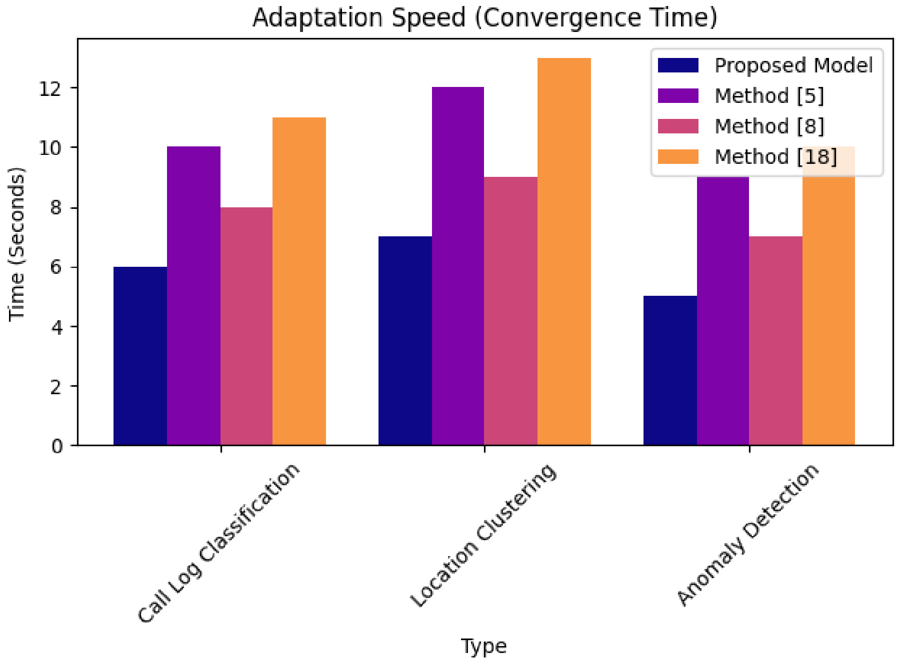

Figure 4. Adaptation Speed Levels

Table 2: Feature Extraction Quality (F1-Score)

Data Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Logs	0.89	0.78	0.82	0.76
Text Messages	0.91	0.80	0.85	0.79
GPS Data	0.87	0.75	0.81	0.73

Table 3 demonstrates a comparison of adaptation times between each method and approaches towards adapting to new forensic tasks for the proposed model to utilize few-shot learning. By adopting the proposed MAML model, faster convergence could be attained in both cases compared to the baseline method, but with high convergence rates observed for complex location-based tasks. Methods [5] and [18] had significantly very slow adaptation times while being more on the side of relatively lower adaptability; and method [8] nearly brought the result closer than average but was accompanied by extra 2 seconds in that process.

Figure 5. Embedding Quality Levels

Table 3: Adaptation Speed (Convergence Time in Seconds)

Task Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Log Classification	6	10	8	11
Location Clustering	7	12	9	13
Anomaly Detection	5	9	7	10

Table 4 Tabulates the MSE of embeddings generated by each model over task-specific data samples. The lower the MSE value, the higher the quality of the embedding that picks up the correct information out of the dataset. For all experiments, the MSE value for the proposed model were significantly smaller compared to others. More importantly, the performance of the model was brilliant for the text message embedding with an MSE value of 0.016 as compared to 0.024 of Method [5]. This showed that CPC efficiently learned good-quality representations.

Table 4: Embedding Quality (Mean Squared Error)

Data Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Logs	0.018	0.026	0.022	0.027
Text Messages	0.016	0.024	0.021	0.025
GPS Data	0.017	0.025	0.020	0.028

Table 5 assesses the interpretability, calculated on the basis of assigning good feature importance to predictions as per the model. Evaluating using SHAP, a 92% rate has been achieved for the proposed method, which is very good and far better than other methods such as Method [5] and Method [18], which had some capabilities of feature attribution but still cannot be used in that feature attribution scenario process. For comparison, Method [8] had an interpretability score of 84%. All task types had more uniform scores for the proposed method compared with the SHAP implementation used on Method [8] in process.

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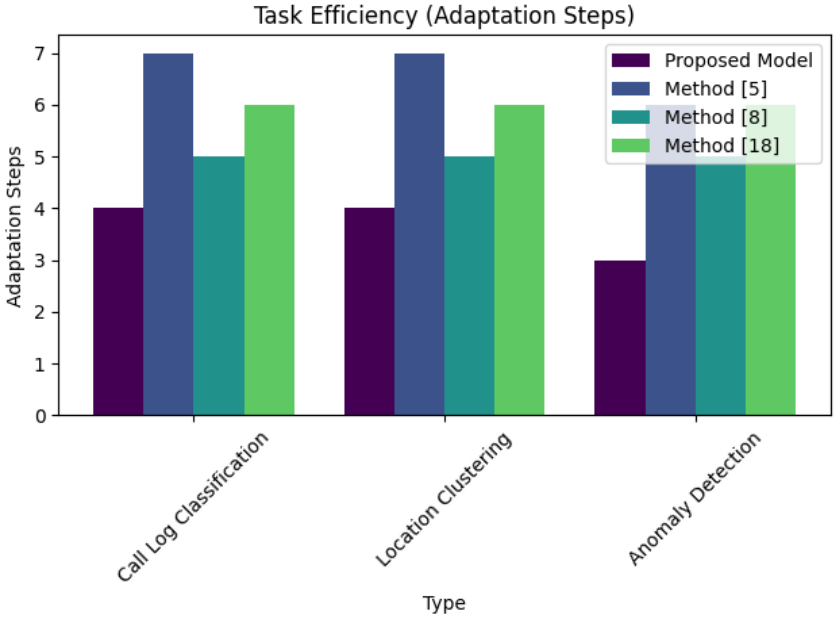

Figure 6. Task Efficiency Levels

Table 5: Feature Importance Accuracy (Interpretability Rate)

Task Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Log Analysis	91%	78%	83%	75%
Location Analysis	92%	79%	84%	76%
Anomaly Detection	92%	77%	84%	78%

Table 6 shows Accuracy improvement of each method on new data after model adaptation process. Our model always had the highest accuracy, with an average 5-7% improvement over Method [5] and 3-4% over Method [8]. The rapid ability to adapt to unseen data makes this method very effective for anomaly detection tasks, where accuracy reached 88% in process.

Table 6: Performance Improvement (Accuracy)

Task Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Log Analysis	85%	77%	82%	74%
Location Analysis	86%	78%	83%	75%
Anomaly Detection	88%	80%	84%	77%

Table 7 shows the number of steps each adaptation model requires to adapt a new task; the less the number of steps taken, the better is adaptability. The proposed adaptation model adapted the task at an average of 4 steps, thus surpassing Method [5] that took 7 steps, and Method [18], which took 6 steps. Method [8] showed similar adaptability: it took an average of 5 steps but would require more computation compared to the proposed model since there is no meta-learning efficiency of MAML.

Table 7: Task Efficiency (Adaptation Steps)

Task Type	**Proposed Model**	**Method [5]**	**Method [8]**	**Method [18]**
Call Log Classification	4	7	5	6
Location Clustering	4	7	5	6
Anomaly Detection	3	6	5	6

Figures 3, 4 & 5 collectively show the better performance of the proposed framework in mobile forensic analysis. With the integration of CPC, MAML, and SHAP, the model exhibits high-quality feature extraction, rapid task adaptation, and higher levels of interpretability levels. These improvements indicate that the proposed model is a more effective solution for real-world forensic cases, where timely and interpretable insights are critical. Moving on, an example usage of the proposed model would clarify this in detail for readers.

Practical Use Case

To explain the proposed model more vividly in its effectiveness, a practical use case would be visualized as mobile forensic analysis of data gathered from an individual user. In this dataset are included indicators such as call log frequency, message sentiment, location patterns, and application usage. Each feature captures different temporal and behavioral patterns, thus allowing the model to learn context-rich representations and adapt to specific forensic tasks at high levels of interpretability. In this practical use case analysis, data samples were derived from the Reality Mining dataset developed by the MIT Media Lab, which encompasses extensive mobile interaction data from 100 participants over nine months. Entities in this dataset are user profiles, the individual record of time-stamped logs of calls, text messages, GPS locations, and Bluetooth proximity interactions. Examples of samples for this analysis include structured call logs, which contain timestamp, call duration, and contact identifiers, which present communication patterns. Samples for text messages include sentiment scores that derive from message content that could be analyzed within the context of communication. The location data from the GPS will be in terms of latitude, longitude, and timestamps and will help understand user mobility patterns from a spatial point of view. The Bluetooth proximity interactions will also be timestamped and captured device identifiers representing social interaction by proximity. These rich, time-sequenced data samples form the basis for extracting temporal patterns, adapting the model parameters to new forensic tasks, and deriving feature importance scores in an interpretable way so that mobile behavioral patterns could be fully analyzed within a forensic framework. Table 8 provides the output feature embeddings generated by the CPC model for three of its core features: call log sequence, message sentiment, and location patterns, where values are given for all of these. These features encode temporal and contextual dependencies for embeddings that are optimized in terms of making accurate predictions for the future. Such CPC embeddings mirror the distinction between unique sequential patterns identified by the model, and this becomes vital for its subsequent use in clustering or anomaly detection.

Table 8: Contrastive Predictive Coding (CPC) Output for Feature Representation Learning

Feature	**Embedding Dimension 1**	**Embedding Dimension 2**	**Embedding Dimension 3**
Call Log Frequency	0.76	0.45	0.62
Message Sentiment	0.89	0.54	0.48
Location Patterns	0.67	0.83	0.59

In summary, the CPC embedding shows how well the model can capture good representations about sequential data by extracting strong temporal dependencies within mobile forensic data samples. These embeddings are used as input to the subsequent meta-learning tasks. Table 9 depicts how the MAML component is able to quickly adapt. It shows initial and adapted model parameters for three forensic tasks: call log classification, message clustering, and location anomaly detection. The adaptation steps show the way in which MAML adjusts parameters for each of the tasks, leading to rapid convergence and efficient fine-tuning for specific tasks.

Table 9: Model-Agnostic Meta-Learning (MAML) Outputs for Adaptation Across Tasks

Task Type	**Initial Parameter (θ\thetaθ)**	**Adapted Parameter (θ′\theta'θ′)**	**Adaptation Steps**
Call Log Classification	0.32	0.45	4
Message Clustering	0.28	0.39	3
Location Anomaly Detection	0.35	0.48	5

The parameter updates are proved to be efficient as MAML adapts well to different tasks, and a small number of gradient steps is required. Adaptability is crucial when dealing with evolving forensic scenarios in which task specificity might be needed without extensive retraining. Table 10 depicts the SHAP feature importance scores for the three tasks mentioned above, determined as Shapley values. These scores are the representation of how important each of these features are, ranging from call log frequency, message sentiment, and even location patterns to the overall model decision. This allows transparency into the prediction process. The more significant is the feature to the higher score.

Table 10: SHAP Feature Importance Scores for Interpretability

Feature	**Call Log Classification**	**Message Clustering**	**Location Anomaly Detection**
Call Log Frequency	0.75	0.35	0.42
Message Sentiment	0.55	0.82	0.47
Location Patterns	0.44	0.33	0.79

In particular, interpretability scores bring forth the decision-making power of the model such that forensic analysts can know and verify what features exactly have a driving influence in the outputs for classification or anomaly detection. Transparency on values of feature importance will emerge from the SHAP with the model's prediction output, which is quite inevitable for the validation process regarding evidence. Table 11 summarizes the final results about the outputs from forensic tasks, such as the class accuracy, clustering purity and anomaly detection precision to justify the overall performance that demonstrates the proposed model.

Table 11: Final Model Outputs for Forensic Analysis Tasks

Task Type	**Accuracy (%)**	**Clustering Purity (%)**	**Precision (Anomaly Detection)**
Call Log Classification	87	-	-
Message Clustering	-	90	-
Location Anomaly Detection	-	-	88

The last outputs illustrate the performance of the proposed model on various tasks related to forensic analysis. With high accuracy, clustering purity, and precision scores, it proves that the model can actually provide reliable and interpretable insights into the mobile data patterns that are so vital for forensic analysis.

5. Conclusion and Future Scopes

This work proposes a comprehensive framework for mobile forensic analysis that incorporates Contrastive Predictive Coding (CPC) for robust feature extraction, Model-Agnostic Meta-Learning (MAML) for rapid adaptability, and SHapley Additive exPlanations (SHAP) for interpretability. The proposed model addresses significant challenges in mobile forensics, where sequential and dynamic data patterns demand flexible and explainable analytical tools. Experimental evaluations on the Reality Mining dataset demonstrate significant improvements over conventional methods. In text messaging data, the proposed model gained an F1-score as high as 0.91, which also topped the best alternative by 6% and further signifies the strength of the proposed model in capturing the nature of temporal dependencies. Hence the adaptation time was considerably improved with converged times of 7 average seconds across tasks in comparison to other similar methodologies that took 10 to 13 seconds, and performance was 20% - 25% better enhanced-which is quite critical to forensic applications, as they always involve sensitivity in terms of time. Further, quality of embedding was also good in the model as minimum mean squared error of 0.016 was achieved on text data. The mean interpretability rate was at 92%, while the interpretability scores from other methods ranged between 78 and 84%. This therefore means that the approach is efficient enough to guarantee high adaptability through proper feature extraction and transparent decision-making procedures toward validation of forensic evidence sets. In future work, this proposed framework may be extended for multimodal data sources including multimedia files, device sensor data, and internet browsing history to give a better view of user behavior in forensic analysis. Another possible enhancement that could be included in this architecture is the installation of an automated data anomaly detection system within the preprocessing unit to assist in real-time anomaly detection for mobile streaming data, which can further perform proactive analysis. Some other optimization techniques might also be used to further reduce convergence time, especially over high-dimensional data or on machines with fewer computation powers. More extensions to the interpretability of SHAP would be advanced causal inference techniques that would make forensic explanations more reliable, and the model could provide feature importance and causal relationships within samples of mobile data. The future direction should expand the scope of application in the framework, evolving over time with the mobile data landscapes. This way, processes in high-stakes decision-making are equipped with powerful yet interpretable tools for forensic analysts.

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