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Methodology Article

Closing the Gap on Addiction Recovery Engagement with an AI-infused Convolutional Neural Network Technology Application—A Design Vision

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Abstract

Currently, real-time detection networks elaborate the technical details of the Faster Regional Convolution Neural Network (R-CNN) recognition pipeline. Within existing R-CNN literature, the evolution exhibited by R-CNN is most profound in terms of computational efficiency integrating each training stage to reduce test time and improvement in mean average precision (mAP), which can be infused into an artificially intelligent (AI), machine learning (ML), real-time, interactive, recovery capital application (app). This article introduces a Region Proposal Network (RPN) that shares full-image convolutional features with a real-time detection AI-ML infused network in an interactive, continuously self-learning wrist-wearable real-time recovery capital app for enabling cost-free region proposals (e.g., instantaneous body physiological responses, mapped connections to emergency services, sponsor, counselor, peer support, links to local and specific recovery capital assets, etc.). A fully merged RPN and Faster R-CNN deep convolutional unified network in the app can simultaneously train to aggregate and predict object bounds and objectness scores for implementing recovery capital real-time solutions (e.g., baseball card scoring dashboards, token-based incentive programs, etc.) A continuous training scheme alternates between fine-tuning RPN tasks (e.g., logging and updating personal client information, gamification orientation) and fine-tuning the detection (e.g., real-time biometric monitoring client's behavior for self-awareness of when to connect with an addiction specialist or family member, quick response (QR) code registration for a 12-step program, advanced security encryption, etc.) in the interactive app. The very deep VGG-16 model detection system has a frame rate of 5fps within a graphic processing unit (GPU) while accomplishing sophisticated object detection accuracy on PASCAL Visual Object Classification Challenge (PASCAL VOC) and Microsoft Common Objects in Context (MS COCO) datasets. This is achieved with only 300 proposals per real-time retrieved data capture point, information bit or image. The app has real-time, infused cartographic and statistical tracking tools to generate Python Codes, which can enable a gamified addiction recovery-oriented digital conscience. Faster R-CNN and RPN can be the foundations of an interactive real-time recovery capital app that can be adaptable to multiple recovery pathways based on participant recovery plans and actions. This paper discusses some of the critical attributes and features to include in the design of a future app to support and close current gaps in needed recovery capital to help those who are dealing with many different forms of addiction recovery.

Keywords

Convolutional Neural Networks, Recovery Capital, Addiction Recovery, Artificial Intelligence, Region Proposal Networks, Faster R-CNN, Python

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1. Introduction

The addiction recovery community is grounded in a foundation of support systems that include organizations, families, peers, and social supports. These can be linked to social networks that span personal, spiritual, athletic, occupational, and economic-based relationships [1, 2]. At the core of this foundation of support systems is a fabric of social capital, consisting of the bonding agents that help form relationships and trust and link individuals needing recovery support in a common battle to overcome addiction [3]. In this addiction-centered context, the most pertinent form of social capital is recovery capital, which has been defined as “all the internal and external resources that a person can access in support of their recovery process” [4]. In fact, as Best and colleagues noted, recovery capital can be considered across three domains: “personal capital (qualities such as self-esteem and resilience), social capital (based on the networks and supports that the individual can draw on), and community capital (referring to the resources from the local community that can be accessed such as reasonable housing, training, and employment opportunities),” [5]. One element of community capital is the 12-step mutual aid programs that exist in sober living centers, faith-based organizations, and recovery community organizations (RCOs) across the nation and the globe. For the purpose of this prospective study, 12-step mutual aid programs represent a key element of trust building within a given community’s (in-person or virtual) recovery capital system [6]. Many of these programs, both throughout Florida and locally, are open to the public yet maintain the anonymity of their participants.

1.1. Problem Definition

Recognizing the importance of each of these domains in a person’s recovery journey, what is it that undermines the growth and strengthening of recovery capital for any individual? Relapses are a common complication that may occur in one’s recovery journey when triggered by specific events and occurrences [7]. Though a stronger network of support (albeit in-person or technology-enabled) that helps address biopsychosocial mechanisms can positively impact behavior changes, when unanticipated events or situations occur, they can trigger relapses that diminish recovery capital across its three domains and lead to poor health outcomes [8, 9]. One element that may disrupt this process is that of incentivization. People are incentivized by different things (health, finances, relationships, spiritual support etc.), and identifying and creating incentivization mechanisms has been proven to be a strong component of long-term recovery [10]. Therefore, recovery capital can be strengthened through incentives and a continuous learning tool that becomes a form of “digital conscience”, or virtual mentor, to aid and help motivate participants stay on track in their recovery journeys.

1.2. Technical Innovation

In the interactive recovery capital app, we will employ the innovative algorithm introduced by Ren et al., which introduces Regional Proposal Networks (RPNs) [11]. By computing proposals within a deep net and sharing convolutional layers with object detection networks at test-time, computation is virtually absent of cost [11]. The proposed implementation within an interactive recovery capital app is novel would be nature. Based on Jacob et al., the convolutional feature information maps used by region-based detectors can be employed for generating robust region proposals in an interactive, web-configurable, real-time, artificial intelligence (AI)-machine learning (ML) dashboard app [12]. On top of these convolutional features, the construction of the recovery capital app using an RPN by adding additional convolutional layers that simultaneously regress region bounds and objectness scores at each location on a county-level, 1 kilometer (km) x 1km stratified grid is proposed [11]. Hence, the proposed RPN in the interactive, real-time app would be a fully convolutional network that will be trained end-to-end specifically for the task of optimizing real-time information detection proposals for data capture points, including humanistic, recovery capital-relevant values a client may possess. The RPNs will be designed to efficiently predict region proposals with a wide range of scales and aspect ratios.

The proposed technical innovation will be rooted in the creation of an AI-infused interactive application (app) that invokes the use of many real-time, advanced machine learning and geolocation cartographic and statistical tracking tools to generate a gamified addiction recovery-oriented digital conscience to support any end user with a need to strengthen their recovery capital.

1.3. Algorithms

Recent advances in AI-ML classifiers, such as signature maximum likelihood classifiers and stochastic/deterministic interpolators, allow for infusion into a recovery capital-oriented web-configurable, and customizable app for providing real-time information such as the geographic locations of hospitals, detox facilities, treatment centers, crisis centers, and sober living facilities relative to the location of the user in real time. These classifiers can archive and analyze information that promotes the resolution of alcohol and drug problems such as overdose. This functionality may be supplemented by personal data gathered in real-time, such as physiological response data, previously logged messages, and other clinical and nonclinical information. These technological advances can aid in meshing these and other information data capture points in a web-configurable and interactive app available on both wearable and mobile devices, which can help recovery capital programs by allowing a client to receive customizable treatment (i.e., a habitat modification technique such as digitized token dispensing for attending a 12-step meeting or achieving addiction recovery milestones) from a self-learning app that continuously monitors, trains, and learns from a person's personal activity. Recovery capital can be strengthened with incentives to aid in motivating participants in their recovery journeys [10].

Advances in the field, such as Faster R-CNN (Regional Convolution Neural Network), can upgrade standard R-CNN in a real-time recovery capital app [13]. Faster R-CNNs take advantage of a graphic processing unit (GPU), while the region proposal methods are usable in standard AI and ML-infused apps [12]. Non-graphical uses of GPUs in a Faster R-CNN-enabled, web-based mobile app would include the training of neural networks and real-time data mining for multiple recovery capital-related incentives. Examples of data uses include:

1. Keeping people invested in their personal recovery based on any unit of time,
2. Providing an evidence-based measurement of behavioral and clinical health in real time to a recovery specialist, and
3. Demonstrating quality assurance and oversight for the "product" that jails, hospitals, detox and treatment centers, and sober living homes are "producing" when they treat a person with a substance use disorder (SUD) or other addiction disorder.

A convolutional neural network (CNN) is a deep learning network architecture that directly utilizes input data to learn [14]. Many state-of-the-art techniques in real-time data processing rely on the notion of CNNs, for which a brief overview is provided here [15]. CNNs consist of two components-data extraction part and classification. During information data extraction, the network performs a series of convolutions and pooling to retrieve the critical data feature attributes for aiding in classification [16]. The convolution layers can extract app data feature attributes such as capture point sentinel site geographic locations (e.g., detox treatment center, 12-step meeting center, county emergency hospital) by performing convolution operations with the use of filters to generate a feature model from the input data (i.e., standard outcome indicator metrics that measure ongoing growth and community integration). Each convolution layer in the proposed interactive recovery capital app would have three dimensions: width, height, and depth. Typically, the data would contain *n* filters, where the filter size would be *(a, b, c)*. *a* and *b* would be the width and height of the filter, and *c* would represent the number of channels to process the app-retrieved data [16].

Best and Hennesey surmised that there are four areas concerining the implementation of the concept of recovery capital which must be expanded upon in future addiction recovery literature: Elaboration on the conceptual interactions between recovery capital domains, empirical testing of the conceptual rigor, methods of application in a clinical addiction recovery setting, and the dissemination of recovery capital information to policymakers, practitioners, and lived experience groups [4]. Through the inclusion of the above algorithmic advances the CNN within the real-time, interactive, web-configurable recovery capital app would possess the capability to optimally aid in in accomplishing each of these objectives.

1.4. CNN Integration in the Architecture

The state-of-the-art techniques in real-time data processing rely on the concept of convolutional neural networks (CNNs) [15]. Herein, an overview of the application of CNNs in an interactive, web-configurable mobile app focused on recovery capital is provided, as discussed in this article. As mentioned, there are two components to such an application design—feature extraction and classification. During the app's real-time data meshing and feature extraction, the network would perform a series of convolutions and pooling to assess recovery capital on an ongoing basis (for example, regressively quantifying real-time retrieved, capture point, information data feature attributes, such as georeferenced behavioral empirical data, collected from every aspect of the token collection process).

The convolution layers would extract feature attributes from empirical recovery capital sample datasets by performing convolution operations utilizing filters on the input data (e.g., nonfungible tokens (NFTs) created by a person in recovery) to generate prognosticative, visible, and diverse local recovery role models and other pertinent data (e.g. prognosticative, cartographically delineated, georeferenceable, internal and external resource variables for determining where to initiate and sustain a substance use disorder recovery program at the county level, etc.). Typically, the signature data would contain *n* filters, where the filter size is *(a, b, c)*, where *a* and *b* are the width and height of the filter, and *c* represents the number of channels employed to process the data [16]. Each filter would be independently convolved on the input data, which would subsequently be followed by pooling to generate a real-time, recovery capital-oriented, personal vulnerability model for determining treatment protocol features (potential assertive linkage to recovery mutual aid groups, ongoing recovery check-ups to identify if there is an alternative option to inpatient or residential treatment, etc.). The pooling layer would aid in reducing the size of the input data and recovery capital-oriented data capture point feature attributes. After the filter size is chosen, the stride size would be chosen. Stride size is the size of the step by which the filter moves across a selected data feature attribute [11]. The convolution process in the recovery capital smartphone interactive app would be worked by computing a dot product between the filter and the local region of the data input on which the filter would be implemented. Since deep convolutional neural networks contain several convolution layers, each layer employed in the interactive app would have different filter sizes [16]. As such, varying recovery capital data information capture points would be integrated together in the app, which would act as the final output of the convolution layer.

2. Design Project Aims

One potential research aim for the interactive research capital app design project would be to enable scaling up the signature recovery capital app development (e.g., from a county-level capture point sentinel site to the state and country level). Among the AI components in this technique in the baseline proposal would be the successful training of the Faster R-CNN by employing trained, real-time retrieved recovery capital client information to detect and locate sources of intervention.

Another aim in a technical design effort for such an app would be to address the diffusion of real-time, retrieved recovery capital information about potential georeferenceable hot spots (for example, urban parks where opiate usage and sales transaction occurs) based on field-verified, county-level location data in a designated county geographical area with massive data dissemination on platforms such as X (formerly known as Twitter), Instagram, YouTube, Reddit, and Gab. A design and testing team could analyze engagement and interest in the real-time monitoring of scalable, signature-retrieved, recovery capital input data and provide a differential assessment of the evolution of discourse regarding a county-wide scale for each platform and its users. One key objective could be to promote client, sponsor, recovery specialist, and other collaborator relationships on ChatGPT's space by using the app, for example, to determine possible consequences of health-related threats (such as relapse-induced overdoses). In addition, the impact that this tool may have on real-time recovery capital research and policy development by disseminating information through an app's preprint servers can allow for rapid media coverage and a consequent impact on implementing control choices. Design team efforts would fit information spreading with potential, real-time-generated recovery capital data and information models for each social media platform. It is hypothesized that newly introduced features in the proposed recovery cap app (such as live internet browsing and plugins) can facilitate a more seamless interaction with invaluable insights for implementing a real-time source, as well as the management of any specific addiction recovery community populations and the stakeholders who support them.

Subsequently, after the convolution layers are infused into the app, a few dense layers would be added for algorithmic classification of all archived recovery capital data input from the client. The neurons here function as a non-linear function that takes multiple inputs, and from them, renders singlular outputs. These neurons, within the dense layers, would be fully connected to all the neurons of the previous layers in the app. The last dense layers in the app would consist of neurons equal to the number of classes. A design effort would classify and render the probability of each class present in all input, real-time retrieved, recovery capital-stratified, capture point data collected and archived by the app (e.g., assessment of recovery capital 50-item scale assessing both Personal Recovery Capital [25] questions and Social Recovery Capital [25] questions) [17]. While the classification of potential county-level treatment centers and two-way communication with a single sobriety specialist is currently available in a web-based app, it alone may not be sufficient to help a client recover from an addiction. It is vital that the role that recovery capital plays in the success or failure of an individual's recovery is acknowledged in the design of recovery apps such as this one [18-22]. Such a real-time app adds another feature in the design phase to predict potential relapse episodes. For example, while a client views the localized data of the closest capture point sentinel site (county hospital) bounded within a solid box in the app, more details (e.g., post-treatment recovery check-ups, dates. early re-intervention candidate) physiological information about the client can be forwarded in real-time to clinical interventionists. This would include the client's exact location based on an embedded GPS tracker in the interactive app. Furthermore, the number of contact specialists, including sponsors, psychological counselors, family members, friends, and other social support network members, would be accessible in real-time.

3. Design and Testing Steps

In this Regional CNN approach, a design and testing team would execute several steps in the proposed recovery capital interactive app which have been challenging for previous sobriety app developers. As with any AI-ML-infused, web-based app development, there is a need for prototype testing and field validation of the new app [23, 24].

First, prototype development may involve training the recovery capital-oriented, temporally dependent datasets (e.g., aggregated social capital empirical data consisting of relationships with family and friends which are conducive to sobriety) using a pre-trained convolutional neural network model for extracting the convolutional feature data from the last layer of the trained network. This step would enable the neural network to understand the key features within the data that separate multiple classes within the app (e.g., re-evaluation of markers of the recovery journey to determine the quality and even duration of successful sustained recovery from addiction).

To train towards neural network feature recognition, Inception V2 is proposed as the base pre-trained convolutional network for precisely extracting the recovery capital-oriented, real-time retrieved data capture point information. Inception V1 (or GoogLeNet) was the state-of-the-art architecture at *ImageNet* Large Scale *Visual* Recognition Challenge (ILSRVRC in 2014. It holds the record lowest error in the ImageNet classification dataset. It is a complex deep learning architecture that uses smart factorization methods to make convolutions efficient in terms of computational complexity. The network performs better when the input dimensions are not changed drastically [25].

3.1. Post Training

For post-training of the app, employing attributes from the input recovery capital data that were the most reflective/useful of the client's circumstances (e.g., actively supporting local movements aimed at increasing recovery support services) is proposed [18]. In order to localize information capture points of interest in the app, a design team should employ the notion of Region CNNs (R-CNNs) [11]. To do so, a few steps would be necessary. First, predefining anchor aspect ratios, which will eventually be scaled to the county level is proposed. The anchors will be emplaced during training of the neural network in the app. For the case of recovery capital data infused into the app, the base anchor size would be set as [256, 256] pixels, with scaling ratios and aspect ratios as [0.25, 0.5, 0.75, 1.0, 1.50, 2.0, 2.5] and [0.25, 0.5, 0.75, 1.0, 1.50, 2.0, 2.5] respectively [19]. The width and height of each anchor in the recovery capital app be set as:

width_anchor = scale[i] * sqrt(aspect_ratio[i]) * base_anchor[0]

height_anchor = scale[i] * base_anchor[1] / sqrt(aspect_ratio[i]),

where *i* is the index of the matrices of scales and aspect ratios [16]. In total, using 300 anchors for training. In so doing, anchors will properly be directed to the RPN is proposed [12]. Here, the task would be to train the network to identify those boxes in the app that are indicative of empirical recovery capital information capture points of interest, which may include locations of local recovery community support institutions and sources of sustained recovery support and early re-intervention [18]. To do so, a design effort would manually ground truth each box before training as a potential recovery capital-oriented feature attribute. The trained anchors for creating retrievable, real-time information data capture point (i.e., recovery schools, recovery industries, recovery ministries/churches) with an “objectness” score and selects the ones that are most likely pertinent to client recovery (e.g., internal qualities that characterize the traits or resources needed to sustain recovery including resilience, coping skills, self-esteem, perceived and actual self-efficacy, and communicative skillsets) based on an empirical score [16].

For post-training (and validation), the RPN would be connected to a convolutional layer with 512 output nodes [16]. These output nodes would be connected to two convolutional layers in the real-time recovery capital interactive app, where one would act as a classifier and another as a regressor. The classifier connected to the RPN would predict the probability of retrieved, recovery capital-oriented capture point data of interest within the anchors, and the regressor would estimate the tight boundary surrounding the corresponding objects using anchors in the app [16]. The design and test effort would fine-tune the classifier by varying learning rates. This would employ the stochastic gradient descent (SGD) solver for 50,000 iterations with a base learning rate of 2e-5. Another 25,000 iterations would then occur by reducing the base learning 2e -6 and the rest 25,000 with 2e-7 for faster recovery capital input data convergence [16]. The learning rate for each iteration is shown in Figure 1.

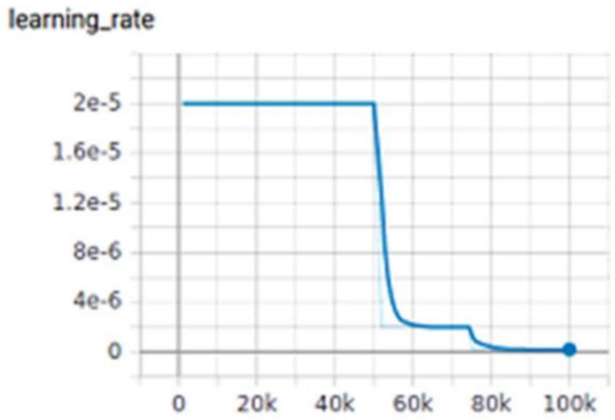

Figure 1. *The learning rate for each iteration in the proposed recovery capital interactive smartphone app.*

During training, the loss function is an important criterion for correctness [11]. The loss function measures the learning ability of a neural network architecture [26]. The goal of training the input recovery capital data is to minimize the loss of training data [16]. In previous real-time app development, Jacob et al. noticed that the default binary cross entropy loss function, which is standard, had increased after 15,000 iterations for training real-time, drone-retrieved signatures of the malaria mosquito oviposition habitats [12]. To minimize the loss, the authors applied a novel focal loss function that penalized instances of false negatives, which in this case was an information data capture point (scaled-up capture point sentinel site breeding site aquatic foci) classified as background. In the proposed interactive recovery capital app, the number of anchors containing real-time retrieved information and data capture points would be minimal compared to anchors containing the background class. Hence, the classifier would not be biased towards any erroneous class in the app, which could result in biased learning [26]. Focal loss is an improvement over the more standard cross entropy loss. This proposed app will perform this computation since it lowers the loss of well-classified cases and emphasizes the misclassified ones [11]. The design team will propose the following equation in the app:

$$Q = \begin{cases} p \; if \; y=+1 \\ 1-p \; otherwise. \end{cases} \tag{1}$$

Here, y would denote the ground truth of the class (+1 for a 12-step town hall meeting and -1 for background), and $p \in [0,1]$, which would be the app-generated model estimated probability for the class label $y = +1$ [16]. This would quantitate focal loss. The designers would add an additional modulating factor $(1-Q)^{\lambda}$ to the above loss to provide tunability, where $\lambda >= 0$. The focal loss (FL) will be defined as $FL(Q)=-(1-Q)^{\lambda}log(Q)$ in the app database.

In this prospective intervention design, when a potential recovery capital information data capture point location of a culturally indigenous support institution is misclassified, and Q is small, the modulating factor would be close to 1, and this would not affect data loss. When Q tends to 1, the modulating factor nears 0, and loss for correctly classified examples is down-weighted [11]. $\lambda=2$ would be the optimal focal loss indicator in the proposed recovery capital app. After applying focal a client would be able to see, as in Figures 2 and 3, minimization of the loss of data information. Essentially, when the loss in training data is similar to the loss in validation data (e.g., in this prospective research, validation data would be used to train the app), then the process of training and validation of the recovery capital, real-time retrieved data capture point would be iterative [26]. The final set of parameters of the neural net architecture would minimize the data loss criteria.

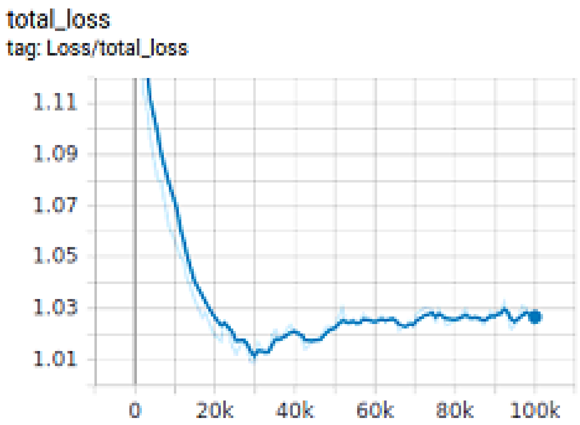

Figure 2. *Total loss graph with focal loss.*

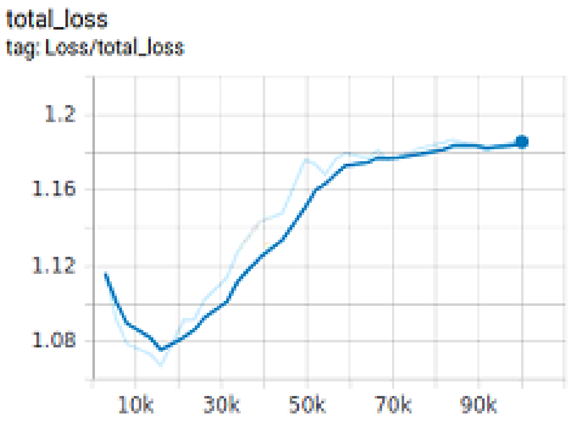

Figure 3. *Total loss graph without focal loss.*

3.2. IoU

Finally, a design team would define a user-understandable metric with the capacity to reveal the quality of the neural network post-trained and validated for implementing recovery capital tactics. The key metric would be an Intersection Over Union (IoU). The IoU metric measures the correctness of a given bounding box [11]. It is, formally, the area of the intersection of the predicted box and ground truth box divided by the area of union of the predicted box and the ground truth box [16]. It is illustrated below in Figure 4, where Green denotes Ground Truth Box, and Red denotes a Predicted Box. The IoU threshold would be set as at least 0.7. In Jacob et al., when the IoU was 1, then a perfect classification and emplacement of the bounding box occurred [12]. Lower IoU values in a web-configurable, interactive dashboard app can indicate poorer performance [11].

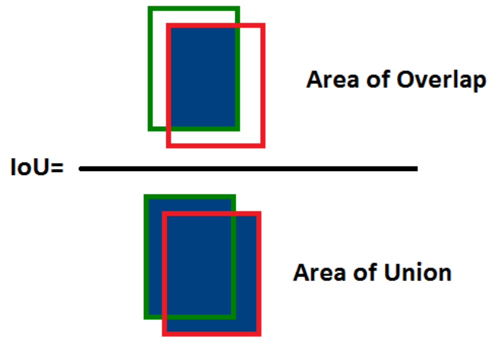

Figure 4. *Forecasted IoU metric measuring the correctness of a given bounding box in a recovery capital app.*

Computing the True Positives, False Positives, and False Negatives for classification in the validation set would allow for the integration of a final metric called *mean Average Precision* or *mAP*. Denoting AP is denoted here as the Average Precision (AP) in finding the area under the precision-recall curve of each real-time retrieved, recovery capital-oriented information data capture point class [26]. The *mean Average Precision* or *mAP* score would be calculated by taking the mean AP over all classes and/or across all IoU thresholds. Precision and Recall are standard metrics in real-time app classification [12]. The precision would be defined as the ratio of True Positives to the Sum of True Positives and False Positives. The Recall would be subsequently defined as the ratio of True Positives to the Sum of True Positives and False Negatives. Classifier accuracy increases with both Precision and Recall [11]. The *mAP* of all recovery capital app retrieved data in the validation set would be determined to 0.87. Note that in Jacob et al., if the authors set the IoU with lower thresholds, which are defined as being less than 0.7, the *mAP* was higher [12].

It is emphasized here that it would be recommended to train the real-time, recovery capital app-generated Faster R-CNN model in using the annotated data to detect and locate sources of solutions (real-time meshing of mental health issue data in order to reach a stable recovery solution). A design and testing team would train and validate the smartphone app using a graphic processing unit (GPU) cluster as in Jacob et al. [12]. The cluster would have four nodes of GeForce GTX TITAN X, each with 12 GB of memory.

Each recovery capital client update would be directed into precious models constructed in the app for classification and localization, which would strengthen expected results using the GPU [16]. The probabilities of detection by the neural network (e.g., the confidence in the app-generated, real-time model in making decisions such as whether a recovery capital client could benefit from individual treatment or extended group support treatment) would be close to 0.99. Not a single false negative will exist in testing the dataset, although a small number of false positives (<10%) would be possible. It may be assumed that with further training, more robust image outputs should be expected.

4. Python Application

The proposed recovery capital app's technical development uses Python, a general-purpose coding language. This means it is designed to be employed in a range of applications, including data science, software and web development, data science, and machine learning [27, 28]. One of the key reasons Python can be favored for an interactive recovery capital app is to maintain uniformity. Such an app becomes easier to develop and maintain when both the back end and front end are written in the same language. The field validation testing of such an app is also accelerated.

The advantages of Python programming infused into an interactive recovery capital app are myriad. Python is a high-level coding language that integrates low-level details in order to make it beginner friendly. This function is immensely useful when designing a project that involves the collaboration of several different specialists with diverse backgrounds. It allows addiction and recovery specialists to have significant input in the development of recovery capital app-based treatment regimens that are customized for their clients while also encouraging the technological, AI/ML-based complexity that such an integrative experience requires.

4.1. Faster R-CNN

The real time information management and detection system within the recovery capital app will be a fully convolutional network with a Fast R-CNN detector which employs proposed regions [11]. The entire recovery app framework will be a single, unified network for real-time information retrieval, information management, and object detection. The neural architecture in the RPN module will tell the Fast R-CNN module where to search for data. The designs and properties of the network for region proposal and develop algorithms for training both modules with features in the app will be introduced.

In the deep, architectural, real-time network system, an RPN will take an image or information bit of any size as input and will output a set of proposals, which will each be assigned an objectness score. A design team will model this process with a fully convolutional network in the app. Both nets within the app will share a common set of convolutional layers in order to preserve shared computation with the Fast R-CNN detection network.

Sliding a small network over the convolutional feature output for the RPNs is proposed. This small network in the app would take as input an n × n spatial window of the convolutional feature recovery capital data information, capture point, signature dataset [11]. Each sliding window will be infused to a lower-dimensional feature (256-d for ZF and 512-d for VGG, with ReLU) [29]. This feature will be fed into two fully connected sibling layers: a box-regression layer (reg) and a box-classification layer (cls) [11]. The design effort will use $n = 3$, noting that the effective receptive field on the input image in the app is large (1 and 228 pixels for ZF and VGG, respectively) [11]. Note that because the proposed mini-network will operate in a sliding-window fashion, the fully connected layers in the app will be shared across all spatial and information datasets, such as those for real-time connection to emergency services, sponsors, counselors, peer supports, and links to local and specific recovery capital assets. This architecture will be implemented in the interactive app framework with an $n \times n$ convolutional layer followed by two sibling 1×1 convolutional layers (for reg and cls, respectively) [11]. The information and image representations derived from pre-trained CNNs will become the new state-of-the-art in computer vision tasks in sobriety-related tasks such as instance retrieval.

The design team will take advantage of the object proposals learned by an RPN in the app and their associated CNN features to build an instance search pipeline, which is composed of a first filtering stage followed by a spatial reranking [30]. The Faster R-CNN features within the network for fine-tuning recovery client's data (e.g., real-time retrieved time signatures of when digital tokens were dispensed and for what task accomplished, quantifying changes in levels of recovery capital to evaluate one's program and their own professional performance) would be employed [18].

The significance of designing and pilot testing a Faster R-CNN optimized recovery capital app lies in its ability to create a novel web- and community-based tool with applications for teenagers and seniors alike who deal with an array of different addictions. Amongst the proposed objectives is that real-time, AI-ML infused, informed, gamified visual design would be able to engage recovery community participants as an incentive-based system to strengthen recovery capital across a socio-ecological spectrum. Incentivizing positive behaviors in an individual's recovery through a mobile application that can be easily accessed throughout the day can encourage natural serotonin and dopamine releases in the brain each time the individual performs one of the positive tasks established for them [4].

4.2. Region Proposal Networks Application

For the purpose of this conceptual discussion, it is hypothesized that introducing novel RPNs that share convolutional layers with state-of-the-art, algorithmic object detection networks infused into an interactive app can aid in implementing recovery capital strategies (e.g., effectively collecting behavioral data from every aspect of the token collection process, geolocating treatment facilities or other recovery resources in real time using the app's website navigation software, or through the GPS functionality. By real time-sharing convolutions at test-time, the marginal cost for computing these proposals would be small (e.g., 10ms per retrieval of a georeferenced recovery treatment capture point, sentinel site, geolocation) [16]. The assumption is that the retrieved recovery capital-oriented, convolutional feature attribute data employed by region-based detectors, such as Fast RCNN, in a web-configurable app can generate such proposals.

On top of these convolutional features, constructing an RPN in an interactive mobile app would allow for adding a convolutional layer that simultaneously regresses region bounds and objectness scores at each georeferenceable, recovery-capital-oriented capture point, employing a stratifiable grid [11]. Hence, the RPN in the app would be a fully convolutional network. These sentinel site recovery capital-oriented information data capture points could be trained end-to-end specifically for the task of generating robust data, which can provide real-time information to clients, family members, and other support specialists. A sample of a use pattern establishing such data capture points will be provided as follows:

1. Create a QR code that can be scanned at meetings halls,
2. Click on the Daily Meditation/ Start your Day Practice – Available to all Pathways hosted on the app,
3. Click on and watch till the end for any of the guided meditations on the app,
4. Click on and watch yoga instructional videos developed by yoga instructors in recovery,
5. Click on and watch/ listen to recovery podcasts,
6. Submission of own recovery support message on the app's social media platform,
7. Completion of a Recovery Capital Assessment,
8. Completion/ update of a Recovery Management Plan, and
9. Complete daily 10th step/ daily positive and negative assessment of the day within the app, and other pertinent data.

4.3. Coding

Coding in interactive apps is a revolutionary technology that has changed the face of programming. This allows users to write code in Python, which is one of the most popular and readily accessible programming languages. With its simple user interface and powerful features, Python can be infused into an interactive, real-time recovery capital app designed to help clients on their journey to recovery. Python coding can enable the construction of real-time, personal capital, and social capital-based graphical models for quantifying changes in levels of recovery capital to evaluate personal performance. The app introduces users to important coding concepts such as recovery capital-related explanatory data variables, loops, and functions for gamification orientation, participant personal data logging, advanced security encryption, and more.

The recovery capital app will be able to transcribe client interviews in real time. This material can then be analyzed thematically by coding and implementing various recovery capital tactics (e.g., baseball card scoring dashboards and Token-based incentive programs for determining alcohol and other drug (AOD) cessation capacity of a client at a particular point in time) [31].

4.4. Unified Network

We will merge RPN and Faster R-CNN into a single network by sharing their convolutional features in the proposed interactive recovery capital app using the recently popularized concept of neural networks with 'attention' mechanisms, where the RPN component tells the unified network where to search [11]. For example, the neural network's 'attention' could be focused on real-time connection to emergency services, sponsors, counselors, peer support networks, links to local and specific recovery capital assets. etc.

For the very deep VGG-16 model, the proposed app information directory and object detection real-time retrieval system will have a frame rate of 5fps while attaining state-of-the-art object detection accuracy on PASCAL VOC and MS COCO datasets with approximately 300 proposals [13].

Jacob et al. noted that faster region-based CNNs can take advantage of GPUs in a real-time, interactive, AI-ML-infused app state-of-the-art object detection network for mapping geolocations of malaria mosquitoes in an agro-pastureland peri-urban ecosystem in northern Uganda employing an unmanned aerial vehicle (UAV) or drone dashboard app [12]. In the proposed recovery capital interactive app, we propose employing fast regional CNNs that take advantage of GPU. An obvious way to accelerate proposal computation is to reimplement it for the GPU [11].

RPN methods would be employed, which will be implemented on the GPU, in the interactive app in Python for fast and accurate runtime, information storage, management, retrieving, and precision predictive signature modeling. This will be a fresh implementation of the Faster R-CNN real-time object and information data, capture point, signature detection model in PyTorch and TensorFlow 2 with Keras. Faster R-CNN remains a foundational work in the field and still influences modern information and object detectors [32]. In the proposed recovery capital app, GPU and tensorflow-GPU will be installed in Keras and Mask R-CNN will automatically employ a GPU.

A conceptually simple, flexible, and real-time generalizable app framework for information retrieval and object instance segmentation for the implementation of recovery capital strategy is proposed. The app will be capable of statistically quantifying recovery capital levels to help determine level of care placement decisions, or family/social recovery capital data variables to determine significance level of covariates such as the readiness of close companions and family members to engage in treatment, transformations in the client's behavior when exposed to supportive environments for sobriety-oriented socializing and leisure, and relational ties to more traditional institutions [18]. The approach efficiently detects stratified, capture point information bits (e.g., logged and updated personal client information for identifying whether sustained and positive recovery outcomes for those with severe AOD problems are more closely linked with community recovery capital than the specific attributes of an individual particular treatment protocol [18]) and or objects (such as tracking tools to generate a gamified addiction recovery-oriented digital conscience) to support any end user with a need to strengthen their recovery capital in an image while simultaneously generating a high-quality segmentation mask for each instance.

The suggested approach aims to enhance the interactive recovery capital app by extending Faster R-CNN by incorporating a dedicated branch for predicting segmentation masks within each Region of Interest (RoI), in synchrony with the existing classification and bounding box regression branches [30].

5. Mask R-CNN

Implementing and training Mask R-CNN is straightforward within the Faster R-CNN framework, allowing for the creation of versatile architecture designs [33]. Introducing a mask branch into the proposed recovery capital app incurs a minimal computational overhead, facilitating a quick system and swift experimentation. The seamless integration of Mask R-CNN as an extension of Faster R-CNN ensures optimal results when constructing the mask branch. Notably, Faster R-CNN was not originally designed for precise pixel-to-pixel alignment between network inputs and outputs. This limitation is particularly evident in the coarse spatial quantization performed by the Region of Interest Pooling (RoIPool), the primary operation for attending to instances during information feature extraction [34]. To fix the misalignment, Kaiming et al proposes a simple, quantization-free layer Region of Interest Align (RoIAlign), that faithfully preserves exact spatial location (e.g., real-time connection for client to emergency ambulatory services for overdose prevention) [30]. Mask R-CNN will be employed in the recovery capital app for real-time retrieval of human physiological responses such as blood pressure and respiration rate. The framework can easily be extended to human physiological vital sign estimation using deep learning-based Object Detection and Instance Segmentation in OpenCV (Python / C++). Mask Region-based Convolutional Neural Network (Mask R-CNN) has demonstrated its viability for integration into real-time app technology [35]. However, the Feature Pyramid Network (FPN) structure is limited by its insufficient channel information, absence of valuable global information, and low-level texture information, resulting in the mask branch's inability to capture essential local-global information [35]. In traditional sobriety apps, Mask R-CNN faces challenges in achieving high-quality masks and accurate instance category classification. To address this issue, we suggest the adoption of the Information-enhanced Mask R-CNN, referred to as IEMask R-CNN in the recovery capital app. Within the FPN structure of IEMask R-CNN, the information-enhanced FPN is incorporated to amplify the pertinent global information in the channels, as suggested by Bi et al. [35]. This can include internal and external dimensions and factors, such as aspects inherent to an individual, shaped through interactions with others, and influenced by the broader community-based system [18]. Of the feature information, data capture points help resolve the issues that the high-level feature maps encounter, and useful channel information increases the accuracy of instance category classification [35]. The bottom-up path enhancement with adaptive feature fusion will utilize the precise positioning signal in the lower layer to enhance the feature pyramid. In the mask branch of IEMask R-CNN, an encoding-decoding mask head will strength local-global information to gain a high-quality mask [35]. We forecast that the IEMask R-CNN in the recovery capital app will reveal significant gains over Mask R-CNN on any Microsoft Common Objects in Context (MS) COCO dataset. MS COCO is an extensive imagery dataset which contains photos of everyday objects and individuals. It was designed for the purpose of training machine learning models in image object detection [36].

A new dataset with the goal of advancing the state-of-the-art in information and object recognition in an interactive app framework by placing real time retrieved information that tracks the time that has passed since a client has last ingested the substance they are addicted to in addition to object recognition (e.g., county detox center) in the context of real-time app technology for implementing recovery capital tactics at the county-level is presented in this paper. This will be achieved in this proposed development AI app research effort by gathering real time data capture information and images of complex everyday scenes containing common recovery capital related data and objects integrated within the everyday environment. Objects will be labeled using per-instance segmentations to aid in precise object localization. A detailed statistical analysis of random recovery capital, explanatory determinant datasets in comparison to PASCAL and ImageNet would be conducted. Baseline performance analysis for bounding box and segmentation detection results in the recovery capital app will be supplied using a Deformable Parts Model (DPM).

Real time information and object detection systems can supply replicability, allow for ground truth annotation recall, and affect DPM, R–CNN, and Fast R–CNN detection performance in an interactive recovery capital app [37]. Smaller bounding boxes on high-resolution layers with a smaller stride, and vice-versa, can be determined using a conv/deconv structure in the app. DPMs can fully leverage the low-level local details and high-level regional semantics in an information bit and image. Instead of using video frames in this proposed research a reverse content distribution network (rCDN) will be employed for archiving and real time retrieving recovery capital related video streams emerging from multiple content sources (Internet, Spotify X and other social media platforms), leading to highly dynamic video data sharing. Doing so would also help scale-up recovery capital initiatives from small-scale retrospective implementation largely focused on recovery-oriented mutual aid groups, to a respected and replicable county-level program involving multiple methodologies and organizations [4] and increasingly powerful research designs and procedures for the dissemination of recovery capital. The wrist band app would enable real-time meshing of retrieved recovery capital information.

Real-time video and data modeling a keypoint's location (e.g., as a one-hot mask) and adopting Mask R-CNN to predict K masks in the recovery capital app for one for each of K keypoint types (e.g., face left shoulder) is proposed. This task will helps demonstrate the flexibility of Mask R-CNN in the recovery capital app for acquiring and sending a client's real-time bodily physiological responses to a specialist (e.g., paramedic, counsellor, friend). The minimal domain knowledge for human pose will be exploited by the proposed app real time system. Domain knowledge (e.g., models generated from real time biometric monitoring client's behavior for determining self-awareness of when to connect with any of these contacts) will complement this approach is expected.

Incorporating slight adjustments into the recovery capital app's segmentation system when customizing it for keypoints is suggested. For each of the K keypoints of an event, the training target in the recovery capital app will be a one-hot m × m binary mask where only a single pixel for example, will be labeled as foreground [30]. Throughout the training process, minimizing the cross-entropy loss for every observable ground-truth keypoint, utilizing an m2 way SoftMax output is an aim. This would encourage single points (i.e. direction so the nearest detox center for a client from any county location) to be optimally detected in real time [4]. As in instance segmentation occurs in the recovery app, the K keypoints will be still treated independently.

Adopting the ResNet-FPN variant, and a keypoint head architecture in the app is proposed. The keypoint head will consist of a stack of eight 3×3 512-d conv layers, followed by a deconv layer and 2× bilinear upscaling, producing an output resolution of 56×56 [30]. Jacob et al. [12] found that, in alignment with He et al., [30] a relatively high-resolution output is essential for ensuring accuracy and precision in keypoint-level localization. Models will be trained on all COCO trainval35k real-time retrieved app recovery capital data and information capture point bits/images that contain annotated keypoints. These bits and images could include, for example, client responses to the 50-item Assessment of Recovery Capital (ARC) or its shorter, sister version, Brief Assessment of Recovery Capital (BARC-10) both of which are supported by extensive use in clinical recovery settings across a wide range of populations [4].

6. Expected Outcomes

6.1. Ablations Results

The client's keypoint AP (APkp) in the recovery capital app and experiment with a ResNet-50-FPN backbone will be evaluated. Additional backbones will be considered using 62.7 APkp which is 0.9 points higher than any past COCO keypoint detection winner that employed a multi-stage processing pipeline. The app method is considerably simpler and faster than other sobriety apps developed in the literature or currently available on the commercial market as it would have a unified model that can simultaneously predict boxes, segments, and keypoints. The real-time system will be running at 5 fps. Adding a segment branch (e.g., updating recovery capital client personal data log-in categories), will improve the APkp to 63.1 ontest-dev. More ablations of multi-task learning on minival will be trained parsimoniously in the interactive recovery capital app.

Adding the mask branch to both box-only (i.e., Faster R-CNN) and keypoint-only versions will consistently improve tasks in the interactive app. Training and learning multiple tasks will jointly enable a unified system to efficiently predict all outputs in real-time y (e.g., metrics that measure ongoing growth and community integration for residential rehabilitation services, recovery residences and community recovery services, and biometric monitoring client's behavior for self-awareness of when to connect with a contacts Recovery Community Organizations, (RCO) [38].

6.2. RoIAlign

Investigating the effect of RoIAlign has on keypoint detection is proposed. Though this ResNet-50-FPN backbone finer strides (e.g., four pixels on the finest level), RoIAlign in the app may show significant improvement over RoIPool (e.g. increase APkp by four points). This is because real-time keypoint detections are more sensitive to localization accuracy. This will indicate that alignment may be essential for pixel-level localization in the app, including masks and keypoints. Given He et al.'s [30] noting of the effectiveness of Mask R-CNN for extracting object bounding boxes, masks, and keypoints, a robust instance-level tasks in the recovery capital app is expected. The ROIAlign process will involve the following steps in the recovery capital app:

1. Input Feature Map: The process begins with an input feature map, which is typically obtained from the backbone network. This feature map will contain high-level semantic information about the entire image or other data information capture point (e.g., police station, detox center, etc.). As such, a specialist would know where a client is using a GPS tracker in the app in case an emergency response is required.
2. Region Proposals: The RPN will generate region proposals (candidate bounding boxes) that might contain objects of interest within an image (e.g., an emergency room at a local county hospital).
3. Division into Grids: Each region proposal will be divided into a fixed number of equal-sized spatial bins or grids. These grids will be used to extract recovery capital-related features from the input feature map corresponding to the region of interest (e.g., a 12-step meeting location). The extracted data will be used to regularly monitor strengths and emerging capabilities at geolocations associated with improvements in well-being and quality of life.
4. Bilinear Interpolation: Unlike ROI pooling, which quantizes the spatial coordinates of the grids to the nearest integer, ROIAlign uses bilinear interpolation to calculate the pooling contributions for each grid [12]. This interpolation ensures a more precise alignment of the features within the ROI. Such an analysis can quantify temporal relationships between alleviation of pathology symptoms and the accrual of recovery capital.
5. Output Features: The features obtained from the input feature map, aligned with each grid in the output feature map in the app, will be used as the representative features for each region proposal. These aligned features will capture fine-grained spatial information, which is crucial for accurately segmenting recovery capital client data. For determining other recovery capital strategies (e.g., positive peer support networks, volunteering and community engagement, gamification, etc.).

6.3. Interpolation

By utilizing interpolation in the pooling process, ROIAlign within the application will enhance the precision of feature extraction for individual region proposals, addressing and reducing misalignment issues significantly such as problems with physical recovery capital, which is defined by White and Cloud [18] to include "…financial assets, health insurance, safe and recovery-conducive shelter, clothing, food, and access to transportation." The alignment's precision will enable Mask R-CNN to generate more accurate segmentation masks. As a result, ROIAlign will contribute to the strong performance of Mask R-CNN in instance segmentation tasks, which can also lead to improving social and community-level recovery capital through new friendship networks and active utilization of community resources, such as leisure-based centers, community support groups, etc. [4].

6.4. Advanced Training

End-to-end training on the real-time retrieved recovery capital data that is input into the app will be performed. All previous results generated in the app will be used for stage-wise training, such as training RPN as the first stage and Mask R-CNN as the second, as in Ren et al. [11]. End-to-end ('e2e') training that will jointly train RPN and Mask R-CNN in the app will be evaluated. Partial gradients in the RoIAlign layer, disregarding the gradient w.r.t. RoI coordinates will be computed [30]. The expected outcome, based on He et al. [30] should show that e2e training improves mask AP by 0.6 and box AP by 1.2 in the app.

For conducting the ImageNet-5k pre-training, a design team will experiment with various real-time, interactive, recovery capital app models pre-trained on a 5k-class subset of ImageNet instead of the industry standard, which is a 1k-class subset. A five-fold increase in pre-training recovery capital data as compared with other sobriety app construction methodologies contributed to the literature or in the commercial market is prognosticated. As a reference, Sun et al. used ~250× more data information bits and images (300M) and reported a 2-3 box AP improvement on their baselines [11]. In the proposed app construction, only keypoint annotations but no mask annotations will be used. For brevity, ResNet by 'R' and ResNeXt by 'X' are denoted in the app.

6.5. Train-Time Augmentation

Train-time augmentation will include scale training time for further improving results (e.g., determination of sustainability of recovery and early intervention programs, like employee assistance programs, and drug courts, advanced security encryption, etc.). Here, the following approach on the methodology introduced by He et al will be modeled [30]. During training, a scale will be randomly sampled from [640, 800] pixels and increase the number of iterations to 260k (with a proposed learning rate reduced to between 200k and 240k iterations) [30]. Train-time augmentation is expected to enhance mask Average Precision (AP) by 0.5 and box AP by 0.8 in the app. By upgrading the 101-layer Residual Networks with Aggregated Transformations (ResNeXt) to its 152-layer counterpart, an increase of 0.5 mask AP and 0.6 box AP should be observed [30]. This will produce deeper models in the app, which should improve results using COCO.

Using the proposed non-local (NL) model [39], He et al. [30] achieved 40.3 mask AP and 45.0 box AP. This result is without test-time augmentation, and the method currently runs at 3fps on an Nvidia Tesla P100 GPU at test time [30]. The proposed app neural architecture will combine the model results evaluated using scales of [400, 1200] pixels with a step of 100 and on their horizontal flips. This should render a single-model result of 41.8 mask AP and 47.3 box AP [30].

The real-time app construction method waives nearly all computational burdens of traditional Selective Search at test-time; the effective running time for the proposals is projected to be 10 milliseconds [11]. Using the computationally expensive, very deep models generated in the app, the detection method is anticipated to achieve a frame rate of 5 frames per second (fps) on a GPU, encompassing all processing steps. This positions it as a practical real-time detection system, excelling in both speed and accuracy [11].

7. Conclusion

Addiction recovery is a national public health crisis, and the continual occurrence of overdoses significantly impacts the health outcomes of recovering addicts across the United States [40]. There is a tremendous need for more advanced and engaging web-based applications to support the addiction recovery community. The design idea provided herein could be applied to other fields but is described as an example for this community. A combined application of public health perspectives and computer engineering and sciences can help visualize and harness the innovative power of advanced web-based application development needed to solve many grand societal challenges. Applying such expertise to the nationwide addiction crisis can provide evolving opportunities to potentially save lives and improve the quality of life for those struggling with addiction recovery and in need of new tools to strengthen long-term engagement.

The rapid adoption of recovery capital by the addiction recovery community reflects a shift in focus from understanding the processes underlying addiction to quantifying and qualifying them in order to directly address addictive substances [18]. Convolutional feature maps and real time retrieved information data capture points related to recovery capital can be employed by region-based detectors, like Fast R-CNN, for generating region proposals in an interactive app framework. In so doing, the app can help enable the implementation of recovery capital tactics (e.g., baseball card scoring dashboards, token-based incentive programs at the individual client level, which can be shared with multiple specialists, emergency service providers, sponsors, counselors, peer support, links to local and specific recovery capital assets, etc.). It is expected that the recovery capital app will have a contagious quality since it will transform addiction treatment into a more recovery-focused, human-centered and holistic system of care. As this real-time, mobile, interactive app permeates the field of addiction treatment, it is expected that this technology will help solve societal challenges like sustaining addiction recovery.

Abbreviations

AI: Artificial Intelligence
App: Recovery Capital Application
APkp: Keypoint AP
ARC: Assessment of Recovery Capital
BARC-10: Brief Assessment of Recovery Capital
CNN: Convolutional Neural Networks
DPM: Deformable Parts Model
Faster R-CNN: Faster Regional Convolution Neural Network
FCN: Fully Convolutional Network
FL: Focal Loss
FPN: Feature Pyramid Network
GPU: Graphic Processing Unit
ILSRVRC 2014: *ImageNet* Large Scale *Visual* Recognition Challenge
IEMask R-CNN: Information-enhanced Mask R-CNN
IoU: Intersection Over Union
mAP: Mean Average Precision
Mask R-CNN: Mask Region-Based Convolutional Neural Network
ML: Machine Learning
MS COCO: Microsoft Common Objects in Context
NFT: Nonfungible Tokens
NL: Non-Local
PASCAL VOC: PASCAL Visual Object Classification Challenge
QR: Quick Response
rCDN: Reverse Content Distribution Network
RCO: Recovery Community Organization
R-CNN: Regional Convolution Neural Network
RoIPool: Region of Interest Pooling
ResNeXt: Residual Networks with Aggregated Transformations
RoI: Region of Interest
ROIAlign: Region of Interest Align
RPN: Region Proposal Network
SGD: Stochastic Gradient Descent
SUD: Substance Use Disorder

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Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Anderson, M., Devlin, A. M., Pickering, L., McCann, M., and Wight, D. (2021). 'It's Not 9 to 5 Recovery': The Role of a Recovery Community in Producing Social Bonds that Support Recovery. *Drugs: Education, Prevention and Policy*. 2021, 28(5), 475-485. https://doi.org/10.1080/09687637.2021.1933911

[2] Martinelli, T. F., van de Mheen, D., Best, D., Vanderplasschen, W., and Nagelhout, G. E. Are Members of Mutual Aid Groups Better Equipped for Addiction Recovery? European Cross-Sectional Study into Recovery Capital, Social Networks, and Commitment to Sobriety. *Drugs: Education, Prevention and Policy*. 2021, 28(5), 389-398. https://doi.org/10.1080/09687637.2020.1844638

[3] Weston, S., Honor, S., and Best, D. A Tale of Two Towns: a Comparative Study Exploring the Possibilities and Pitfalls of Social Capital Among People Seeking Recovery from Substance Misuse. *Substance Use & Misuse*. 2018, 53(3), 490-500. https://doi.org/10.1080/10826084.2017.1341925

[4] Best, D., Hennessy, E. A. The science of recovery capital: where do we go from here? *Addiction*. 2022, 117(4), 1139-1145. https://doi.org/10.1111/add.15732

[5] Cano, I., Best, D., Edwards, M., and Lehman, J. Recovery capital pathways: Modelling the components of recovery wellbeing. *Drug and Alcohol Dependence*. 2017, 181, 11-19. https://doi.org/10.1016/j.drugalcdep.2017.09.002

[6] Majer, J. M., Jason, L. A., and Bobak, T. J. Understanding Recovery Capital in Relation to Categorical 12-Step Involvement and Abstinence Social Support. *Addiction Research & Theory*. 2022, 30(3), 207-212. https://doi.org/10.1080/16066359.2021.1999935

[7] Vanderplasschen, W., Best, D. Mechanisms and Mediators of Addiction Recovery. *Drugs: Education, Prevention and Policy*. 2021, 28(5), 385-388. https://doi.org/10.1080/09687637.2021.1982521

[8] Revill, A. S., Patton, K. A., Connor, J. P., Sheffield, J., Wood, A. P., Castellanos-Ryan, N., and Gullo, M. J. From Impulse to Action? Cognitive Mechanisms of Impulsivity-Related Risk for Externalizing Behavior. *Journal of Abnormal Child Psychology*. 2020, 48, 1023-1034. https://doi.org/10.1007/s10802-020-00642-7

[9] Abrantes, A. M., Blevins, C. E. (2019). Exercise in the context of substance use treatment: key issues and future directions. *Current Opinion in Psychology*. 2019, 30, 103-108. https://doi.org/10.1016/j.copsyc.2019.04.001

[10] McKay, J. R. Making the Hard Work of Recovery More Attractive for Those with Substance Use Disorders. *Addiction*. 2017, 112(5), 751-757. https://doi.org/10.1111/add.13502

[11] Ren, S., Kaiming He, Girshick, R., & Jian Sun. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2017, 39(6), 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031

[12] Jacob, B. G., Loum, D., Kaddumukasa, M., Kamgno, J., Djeunga, H. N., Domche, A., Nwane, P., Mwangangi, J., Borjorge, S. H., Parikh, J., Casanova, J., Michael, M., Mason, T., and Mubangizi, A. Geospatial Artificial Intelligence Infused into a Smartphone Drone Application for Implementing 'Seek and Destroy' in Uganda. *American Journal of Entomology*. 2021, 5(4), 92-109. https://doi.org/10.11648/j.aje.20210504.11

[13] Jacob, B. G., Casanova, J., Asceng, J. R. Health security and malaria: A neural network iOS intelligent platform to create and implement seek and destroy integrated larval source management (ILSM) policies. In *Disruption, Ideation and Innovation for Defence and Security*, Adlakha-Hutcheon, G., Masys, A., Eds. New York, NY: Springer International Publishing; 2022, pp. 179-203.

[14] Ineza Havugimana, L. F., Liu, B., Liu, F., Zhang, J., Li, B., and Wan, P. Review of artificial intelligent algorithms for engine performance, control, and diagnosis. *Energies*. 2023, 16, 1206. https://doi.org/10.3390/en16031206

[15] Krizhevsky A., Sutskever I., Hinton G. E., (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*. 2012, 25, 1097-1105.

[16] Minakshi, M., Bhuiyan, T., Kariev, S., Kaddumukasa, M., Loum, D., Stanley, N. B., Chellappan, S., Habomugisha, P., Oguttu, D. W., and Jacob, B. G. High-accuracy detection of malaria mosquito habitats using drone-based multispectral imagery and artificial intelligence (AI) algorithms in an agro-village peri-urban pastureland intervention site (Akonyibedo) in Unyama sub-county, Gulu District, northern Uganda. *Journal of Public Health and Epidemiology*. 2020, 12(3), 202-217. https://doi.org/10.5897/JPHE2020.1213

[17] Groshkova, T., Best, D., and White, W. The Assessment of Recovery Capital: Properties and Psychometrics of a Measure of Addiction Recovery Strengths. *Drug and Alcohol Review*. 2013, 32(2), 187–194. https://doi.org/10.1111/j.1465-3362.2012.00489.x

[18] [D] White, W., Cloud, W. Recovery capital: A primer for addictions professionals. *Counselor*. 2008, 9, 22-27.

[19] Granfield, R., Cloud, W. The Elephant That No One Sees: Natural Recovery among Middle-Class Addicts. *Journal of Drug Issues*. 1996, 26(1), 45-61. https://doi.org/10.1177/002204269602600104

[20] Granfield, R., Cloud, W. *Coming Clean: Overcoming Addiction Without Treatment.* 1st ed. New York, NY: NYU Press; 1999.

[21] Moos, R. H. Theory-Based Active Ingredients of Effective Treatments for Substance Use Disorders. *Drug and Alcohol Dependence*. 2007, 88(2-3), 109–121. https://doi.org/10.1016/j.drugalcdep.2006.10.010

[22] Kaskutas, L. A., Bond, J., & Humphreys, K. Social Networks as Mediators of the Effect of Alcoholics Anonymous. *Addiction*. 2002, 97(7), 891–900. https://doi.org/10.1046/j.1360-0443.2002.00118.x

[23] Chang, T. Y., Chen, G. Y., Chen, J. J., Young, L. H., and Chang, L. T. Application of Artificial Intelligence Algorithms and Low-Cost Sensors to Estimate Respirable Dust in the Workplace. *Environment International*. 2023, 182, 108317. https://doi.org/10.1016/j.envint.2023.108317

[24] Bermejo-Peláez, D., Marcos-Mencía, D., Álamo, E., Pérez-Panizo, N., Mousa, A., Dacal, E., Lin, L., Vladimirov, A., Cuadrado, D., Mateos-Nozal, J., Galán, J. C., Romero-Hernandez, B., Cantón, R., Luengo-Oroz, M., and Rodriguez-Dominguez, M. A Smartphone-Based Platform Assisted by Artificial Intelligence for Reading and Reporting Rapid Diagnostic Tests: Evaluation Study in SARS-CoV-2 Lateral Flow Immunoassays. *JMIR Public Health and Surveillance*. 2022, 8(12), e38533. https://doi.org/10.2196/38533

[25] Lin, T. Y., Goyal, P., Girshick, R., He, K., and Dollár, P. Focal loss for dense object detection. In *Proceedings of the IEEE International Conference on Computer Vision*, Venice, Italy, 2017; pp. 2980-2988.

[26] Jacob, B. G., Habomushiga, P. Location intelligence powered by maching learning automation for mapping malaria mosquito habitats employing an unmanned aerial vehicle (UAV) for implementing “seek and destroy” for commercial roadside ditch foci and real time larviciding rock pit quarry habitats in peri-domestic agro-pastureland ecosystems in northern Uganda. In *Sensemaking for Security*, Masys, A. J., Ed. New York, NY: Springer International Publishing; 2021, pp. 133-148.

[27] Saabith, A. S., Fareez, M. M. M., and Vinothraj, T. Python Current Trend Applications- An Overview. *International Journal of Advance Engineering and Research Development*. 2019, 6(10), 6-12.

[28] Patkar, U., Singh, P., Panse, H., Bhavsar, S., and Pandey, C. Python for Web Development. *International Journal of Computer Science and Mobile Computing*. 2022, 11(4), 36-48. https://doi.org/10.47760/ijcsmc.2022.v11i04.006

[29] Nair, V., Hinton, G. E. (2010). Rectified Linear Units Improve Restricted Boltzmann Machines. In *Proceedings of the 27th International Conference on Machine Learning*, Haifa, Israel, 2010; pp. 807-814.

[30] He K., Gkioxari, G., Dollár, P., and Girshick, R. Mask R-CNN. In *2017 IEEE International Conference on Computer Vision (ICCV)*, Venice, Italy, 2017; pp. 2980-2988. https://doi.org/10.1109/ICCV.2017.322

[31] Braun, V., Clarke, V. Using thematic analysis in psychology. *Qualitative Research in Psychology*. 2006, 3(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

[32] R. Girshick. Fast R-CNN, In *Proceedings of the IEEE International Conference on Computer Vision*, Santiago, Chile, 2015; pp. 1440-1448.

[33] Liu, S., Jia, J., Fidler, S., & Urtasun, R. SGN: Sequential Grouping Networks for Instance Segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, Venice, Italy, 2017; pp. 3496-3504.

[34] He, K., Zhang, X., Ren, S., and Sun, J. Deep Residual Learning for Image Recognition. In *the Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Las Vegas, USA, 2016; pp. 770–778.

[35] Bi, X, Hu, J., Xiao, B., Li, W., and Gao, X. IEMask R-CNN: Information-enhanced mask R-CNN. *IIEE Transactions on Big Data*. 2022, 9(2), 688-700. https://doi.org/10.1109/TBDATA.2022.3187413

[36] Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollar, P., and Zitnick, C. L. Microsoft COCO: Common objects in context. In *European Conference of Computer Vision*. New York, NY: Springer International Publishing; 2014, 740-755.

[37]] Hosang, J., Benenson, R., Dollar, P., and Schiele, B. What makes for effective detection proposals? *IIEE Transactions on Pattern Analysis and Machine Intelligence*. 2016, 38(4), 814-830. https://doi.org/10.1109/TPAMI.2015.2465908

[38] Hennessy, E. A. Recovery Capital: A Systematic Review of the Literature. *Addiction Research Theory*. 2017, 25(5), 349–60. https://doi.org/10.1080/16066359.2017.1297990

[39] Wang, X., Girshick, R., Gupta, A., & He, K. Non-local neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Salt Lake City, USA, 2018; pp. 7794-7803.

[40] Dalphonse, L., Campbell, D. A., Kerr, B. J., Kerr, J. L., and Gadbois, C. More Than an Opioid Crisis: Population Health and Economic Indicators Influencing Deaths of Despair. *Sociological Inquiry*. 2024, 94(1), 45–65. https://doi.org/10.1111/soin.12546