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Menstrual Flow Estimation Using Image-Based Machine Learning

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Abstract—**Estimation of menstrual blood loss (MBL) is a critical component in the diagnosis of HMB, a condition that can produce a substantially decreased quality of life and can lead to complications such as anemia. Methods such as alkaline hemoglobin and pictorial blood loss assessment charts (PBAC) are established, but are expensive, highly subjective, and are not easily used in routine or home settings. Advancements in mobile health based cycle self-tracking have recently paved the way to a more accurate process, despite still being based on user reported data whose accuracy can be affected by recall bias and variability in rating the intensity of flow.**

In this paper, an image-based machine learning approach is proposed for the objective estimation of menstrual flow and viscosity based on the photographs of the sanitary pads. A ResNet-50-based convolutional neural network (CNN) was established with pretraining on 90,000 natural menstrual and artificial pad images generated using realistic variations in viscosity and volume and was used to train/test. The images were pre-processed by standardization, normalization, and augmentation to expand the generalization of the model. Flow groups (light, moderate, heavy) and viscosities (low, medium, high) were labeled and associated with stain pixel-level geometry and color intensity features.

The findings showed very high statistical correlations between the characteristics obtained from the images and the clinical parameters of the flow, with about 85% accuracy with the deep learning classifier. The proposed framework serves as a low-cost, non-invasive, and accessible alternative to traditional practices of monitoring menstrual health. For application purposes, the above can help and allow for early diagnosis of HMB, telemedicine consultations, and providing individuals with a better understanding of their reproductive health from an objective point of view. Future directions involve combinations with wearable sensors and generative augmentation techniques to further increase robustness and scalability to more diverse populations.

Menstrual health, Heavy menstrual bleeding (HMB), Menstrual blood loss estimation, Machine learning, Convolutional neural network (CNN), Image analysis, Sanitary pad images, Viscosity classification, Telemedicine, Digital health.

I. INTRODUCTION

The menstrual cycle is recognized as an important marker of reproductive and general health; however, there remains much complexity in our understanding of it, including one of the least studied aspects, the volume and viscosity of menstrual blood. Determining menstrual flow (volume and viscosity) is essential to establish a diagnosis of heavy menstrual bleeding (HMB), which has traction in both quality of life and potentially represents health events that people are otherwise not forthcoming about. Historically, alkaline hematin analysis and pictorial blood loss assessment charts (PBAC) have been used to assess menstrual loss, but the validity of these measurement tools was compromised limited by subjectivity and specialized equipment, which meant it could never be performed routinely [1]. [2]. Emerging technologies have seen mHealth (mobile health) applications emerge as different methods for menstrual tracking. They can allow the acquisition of real-time data on volume, duration, and symptoms; however, they are based more on user reporting, which is due to recall bias and subjective definitions of different users of what normal flow is [2]. Although these advances are promising because generative modeling techniques have accurately predicted cycle lengths with calibration, manual photographic techniques to confirm volume of menstrual blood are still not being used [3]. Machine learning (ML) has been considered a potentially disruptive technology in the health care industry due to its potential to take advantage of complex data sets for additional analysis. In the case of menstrual health, ML has been shown to predict the onset of the cycle and hormone changes using data from wearable devices [1]. Applying this to the subjective visual analysis of menstrual discharge may act as a unique form of non-invasive monitoring. Notably, ML is capable of providing insight using image ML models, volume, and viscosity measurements from used menstrual products, which could provide new avenues to more objective and quantifiable data regarding menstrual flow profiles. Furthermore, this would bypass virtually all limitations in subjective self-reporting, in addition to allowing broader access to menstrual health assessment without expensive laboratory methods. The outcomes of this research will not just help track personal health; they will provide an accurate means of gathering menstrual health characteristics using predictive models that are robust and reliable. This will provide an early means of intervening on menstrual disorders and other related health issues. In addition, these models can be developed into easy-to-use

web applications, providing empowerment to individuals in managing their reproductive health and contributing to developments in telemedicine. Furthermore, it is likely that using a visual-based machine learning framework for the assessment of menstrual blood can facilitate more rapid diagnosis of conditions like anemia and HMB, which would benefit from timely medical intervention. Furthermore, by integrating the technology(s) we are developing into digital health platforms, individuals will have a more accessible opportunity for menstrual health monitoring because it provides a more accurate, data driven approach than currently available, as well as if we can remove the stigma associated with talking about menstrual health.

This research will develop and validate an image based convolutional neural network which can classify menstrual flow as light, moderate, or heavy from a single image of a used sanitary pad. The network will also characterize the viscosity of blood as low, medium, or high, and relate this information and the geometry of the stains on the sanitary pads to the color metrics at the pixel level. Network performance will be measured through accuracy, sensitivity, specificity, and correlation analyzes on a reference dataset containing real samples and viscosity matched simulants. By demonstrating that low-cost smartphone imaging can produce estimates that are close to laboratory-grade volume estimates, we will explore methods for objective at-home monitoring of heavy menstrual bleeding and the conditions associated with it.

II. LITERATURE REVIEW

Johnson et al. [4] created a menstrual health tracking application to provide women with empowerment through self-awareness and education about their reproductive health. This study tried to meet the needs for reliable menstrual and ovulation tracking systems, since the vast majority of menstrual health applications do not meet user needs and have a significant negative effect on women's health care. The machine learning strategy used was based on the assumption that the reliability of the predicted start date of menstruation would improve with individual cycle data along with the generation of personalized insights for the user. The increase in prediction reliability shown with the application also differentiated it from the wide range of applications out there, providing the user with reliable information regarding their reproductive health. The results also indicated that the application has the potential to promote health and well-being by allowing women to be more educated about their cycle.

Smith et al. [5] have added another study to their extensive investigations on recording menstrual blood loss based on images of contaminated sanitary items for people who had no experience capturing total continuous menstrual flow. The presentation of the work and results achieved validated with image analysis the quantification techniques to determine blood volumes from the images to the nine recorded sequences capturing several images and summating the blood volume collected at the end of the cycle. The results from the study indicated that this application accurately quantified blood volume and the estimates derived from its use were deemed adequate to increase awareness of menstrual health.

Chen et al. [6] made a better prediction of menstrual cycles, relying on self-tracked data from mHealth applications. The study acknowledged being faced with a serious dilemma about identifying true behavior versus self-tracking artifacts due to different levels of user engagement or adherence. A hierarchical generative model was proposed that predicts future cycle lengths, based on previous cycle lengths, and explicitly accounts for missing entries since users may stop tracking their periods. The study made use of a large sample of approximately 186,000 menstruators, and over two million menstrual cycles to evaluate models based on neural networks, and summary statistics. The authors' findings showed that the proposed model delivers state-of-the-art predictions in cycle lengths while also providing methods for unpacking menstrual cycles from self-tracking artifacts. The explicit inclusion of tracking inconsistencies allowed the authors to improve their predictions considerably, especially for the more likely to skip tracking.

Gupta et al. [7] took up the problem of predicting the start date of a menstrual cycle from self-recorded cycle data, since women want individualized menstrual cycle prediction depending on individual physiological patterns. Artificial neural networks (ANNs) analyze information about women's menstrual cycles and individual data to produce population-based parameters for very high accuracy of prediction. The results showed that it predicted very accurately, with an R^2 value of 98.08 and a mean squared error of 1.92, indicating that the neural network correctly modeled the patterns inherent in women's menstrual cycles and thus assisted in the individual prediction.

In an attempt to shed some light on the machine learning potential for accurate period tracking applications, **Thakur et al. [8]** investigated menstrual prediction because any application dealing with women's health management deserves its critical attention. The authors performed a systematic review of the literature and data analysis to assess machine-learning algorithms to improve prediction capabilities in the area. The results showed that the models could identify and analyze menstrual data patterns that form the basis for personalized reminders and notifications to users. Therefore, the authors highlight that the accurate prediction of menstrual knowledge is of paramount importance for improve clinical evaluation and preconceptual care. health management and understanding the menstrual **Josep Perello´ et al. [12]** sought to identify optimal cycle better.

Borzutzky et al. [9] included a clinical data and guideline review allowing the study of HMB causes and management, finding ovulatory dysfunction and coagulopathies as prominent causes. Among inherited bleeding abnormalities, von Willebrand disease remains the most common, with such a high incidence to merit special regard for its investigation and intervention. It remains imperative to distinguish between HMB causes to enable the relevant approach to treatment, i.e., hemostatic medications or hormonal agents. The best form of treatment for HMB in adolescents with bleeding disorders appears to be 52 mg levonorgestrel IUD.

Kadir et al. [10] performed a study on the relationship of the total fluid volume during menstruation to menstrual blood loss and the use of total fluid volume as an approximate method of determining blood loss. The activities of the study were conducted among 53 women who, during two menstrual cycles, analyzed hemoglobin values in menstrual products using the alkaline hematin technique and estimated total fluid volume by means of a very precise weighing procedure. The data showed a good correlation between total fluid volume and blood loss ($r = 0.93$, $p < 0.001$), with blood constituting about 48% of total menstrual flow for women with moderately heavy loss (> 60 mL) and 50% for those with extreme losses (> 100 mL). The regression model relating blood loss to total fluid volume was so accurate that it could allocate 98% of the menstrual periods into the normal, moderately heavy, or excessive blood loss classes. The results suggest that accurate measurement of total fluid volume will provide estimates of actual blood loss, thereby bringing serious implications to cheap commercialization of products to advise patients appropriately.

Atsuko et al. [11] tried to draw attention to the conflict between subjective ratings and gross metric assessments of menstrual flow volumes of Japanese females, hence establishing the void in normative ranges as stated in the 2018 International Federation of Gynecology and Obstetrics guidelines. In a prospective observation study, 211 menstruating volunteers aged 18—49 years were recruited, where 167 women finished three cycles of sanitary napkin weighing for flow amounts recorded by online diaries. There were 497 cycles, and the median total flow was 56.7 g per cycle (5th—95th percentiles: 15.7—166.4 g), with no significant difference. Subjective assessment recognized heavy flow (> 166.4 g) in only 8% of the cases, with the other 92% being labelled as "normal." These values are much higher than those considered useful in a clinical context, and there is a call to raise awareness of this discrepancy in order to clinical tools to assess HMB via the data modeling of a combination of scales. Thus, they evaluated the visual analog scale for heavy menstrual bleeding (HMB-VAS) to assess intensity of bleeding (VASInt) and impact on daily life (VASImp). Existing methods, including the pictorial blood loss assessment chart (PBAC) and the SAMANTA questionnaire, were compared in a logistic regression using data from the validation of SAMANTA. It was found that the HMB-VAS model ($10.86 \times VASInt + 2.48 \times VASImp$) has an accuracy of 86.8%, slightly lower than SAMANTA's 87.9% with similar area-under-the-curve values (0.9396 vs. 0.943). HMBVAS was highly correlated with SAMANTA ($r = 0.798$) and moderately correlated with PBAC ($r = 0.593$), yet weakly with the other two quality-of-life measures (EQ-5D-5L and PGWBI), indicating little concordance with patient-reported well-being. On the other hand, the simplified function ($11 \times VASInt + 2 \times VASImp$), which had an accuracy of 87.6%, affirms the application of the test for rapid screening.

Kadir et al. [13] examined menstrual blood loss and gynecological complications among 116 women with inherited bleeding disorders (66 von Willebrand disease (vWD), 30 hemophilia carriers, and 20 with factor XI (FXI) deficiency), compared to 69 age-matched controls. They used a pictorial blood assessment chart (PBAC) to measure menstrual loss objectively, medical records, and patient interviews. The occurrence of menorrhagia was significantly higher in the study group for vWD, hemophilia carriers, and FXI deficiency (74%, 57%, and 59% respectively), compared to controls (29%). Other amenorrhoeic concerns included longer periods and repetitive flooding. The passage of clots was not significantly different from controls. Approximately 47% of patients sought medical consults for menorrhagia; 36% were treated; and 27% required surgical impediments, with hysterectomies shown to have a 50% complication rate for postoperative bleeding. While lower von Willebrand factor activity (≤ 30 IU/dL) was correlated to higher PBAC scores in patients with vWD, the correlation was not statistically significant and there was no correlation between PBAC scores and severity of bleeds in FXI patients or hemophilia carriers.

Fathima et al. [14] reported the challenges of diagnosing clinically patient based defined objective menorrhagia (menstrual-related blood loss of greater than 80 mL per cycle) and women's health and categorized objective menorrhagia as a leading cause of both gynecological reasons for medical referral and hysterectomies. The authors investigated the methods available to quantify menstrual blood loss while also reporting the limitations of traditional examinations using biochemical testing for alkaline hematin (considered the current gold standard, and impractical, because of cost or storage requirements for clinical purposes) and self-reporting or self-recall (that has been reported to have highly variable, and often, very low reliability, correlating between only 38–76% of subjective complaints with that of objective methods). Other methods, via pictorial chart based scoring forms or weighing of hygiene products, were above-mentioned; yet they remained inconsistent in their observational adherence by end-users and were insufficient in accounting for external loss of a menstrual blood source. The authors reported how the quality-of-life impacts of findings reported as identified by patients relating to social, psychological, or physical practices found in the literature are very far from the volume-based diagnostic criteria; the author present tools combining objective hallmarks and qualitative measures of the collection of this clinical phenomenon of objective menorrhagia.

Janssen et al. [15] thought that to provide an objective diagnosis of menorrhagia, the authors designed and validated a menstrual pictogram that they viewed as easier than the alkaline hematin method, which is the "gold standard" method but viewed as impractical for clinical implementation due to the actual complexity of the method. The research prospectively examined menstruating blood loss measured using their pictogram, compared to alkaline hematin analysis of the hygiene items collected, in 121 women (62 with self-reported heavy bleeding and 59 with normal bleeding). The pictogram and hygiene sampling demonstrated a high level of agreement in estimating blood absorbed in hygiene products demonstrating validation as a reliable method; however, they identified alternate sources of blood loss (clots, etc. or leakages) that were not from absorbed product-blood but were clinically relevant. This reinforces that extreme offering as an enjoyable and inexpensive tool for the clinician does not eliminate the need to include parameters for unreasonable blood loss into clinical evaluations to avoid under-reporting total menstrual blood loss.

Klinzing et al. [16] developed a statistical model considering menstrual diaries, hematological parameters, and patient age to quantify menstrual blood loss (MBL) with the gold standard measurement for MBL quantification, alkaline hematin, which is limited in that it is costly and technically difficult when used for annual reporting by women who complain of abnormal uterine bleeding. They trained mixed linear models in two clinical studies and evaluated the models using an independent cohort. After using alkaline hematin quantification, they derived a correlation of 0.73 with alkaline hematin quantification, while sensitivity and specificity of the model was 87% and 70% for excessive bleeding (> 80 mL/cycle), respectively. The analyses satisfied that it was a detailed complement to the subjective evaluations by physicians and patients concerning quantitative dizziness that is, linking qualitative diaries to an invasive lab-based methods. In fact, in some comparative studies, it was found that pictorial methods like PBACs had better specificity up to almost 94%, but no reliability in measuring total fluid volume or with correlation to quality of life or impact.

Reynolds et al. [17] examined menstrual blood loss (MBL) while the subjects were at a transition phase of menopause, as well as its correlation with cycle irregularity and fluctuations in reproductive hormones. They recruited 77 healthy women in the age group of 21–55 years, with groups subdivided into mid-reproductive age, late-reproductive age, early menopausal transition, and late-menopausal transition women. The total MBL was determined by measuring two separate menstrual blood losses by sanitary products and analysed every week for serum hormones, such as estradiol (E2), progesterone, follicle stimulating hormone (FSH), luteinizing hormone (LH), and inhibins. The results indicated significant variance of MBL across the groups, which moved from mid reproductive age (30 mL) and late-menopausal transition (68.9 mL) associated with ovulatory cycles, to an increase taken at late-menopausal transition. Those cycles then decreased abruptly to 11.80 mL, which showed a significant relationship with cycles, ovulation and volume of blood loss (P = .008). The heavy MBL (> 250 mL) which was linked to the ovulatory cycle showed excessive amounts of E2 and in the late-menopausal transition a different pattern of excessive secretion. The results indicated that MBL is significantly associated with hormonal changes and warrants comprehensive consideration, using well-founded and holistic diagnostic tools-mediation on hormonal-bleeding-type perspectives for clinical management.

Higham et al. [18] attempted to develop and validate an objective method of measuring menstrual blood loss (MBL) under standard conditions to facilitate its use in clinical decision-making for endometrial ablation for menorrhagia. In this trial, 374 women took part from four Yorkshire hospitals, and MBL was measured using the spectrophotometric analysis of the hemoglobin extracted from sanitary products washed by a detergent solution. Women were given their MBL results, and those who proceeded to surgery included women who had electrosurgical endometrial ablation. The results concluded of The 36 women (10%) with normal menstrual blood loss (< 80 mL) who originally declined surgery, the 36 women had not chosen surgery after 27 months. The 292 women with 1-year follow up after ablation, women with true menorrhagia (> 80 mL) improvements which included lower rates of dissatisfaction (9% vs 18%, OR 2.3), hysterectomy (4% vs 7%, OR 1.8). The current evidence supports the fact that an objective measurement of MBL may provide reassurance for women with normal bleeding patterns not to undergo unnecessary surgery and improve the outcomes of women with true menorrhagia.

Recent research has emphasized how machine learning methods are changing the landscape of menstrual health research. For example, MenstruAI's in pad biosensors combine colorimetric chemistry with lightweight convolutional models to quantify C-reactive protein and other markers directly on disposable pads, demonstrating the feasibility of on-device visual analytics. Collectively, these advancements place the menstrual health field in a position of readiness for the current study's focus on pad-image analysis, bridging the divide between wearable physiology and biochemical sensing.

III. METHODOLOGY

A. Data Collection

Images of used sanitary pads were collected for our primary dataset for analysis. Volunteer participants were recruited who were willing to provide sanitary pads to the study for research purposes. Each participant signed informed consent that was authorized under a preapproved ethical protocol wherein menstrual blood images were collected. Each pad was photographed following a standard process -with the same background, lighting, and camera distance in obtaining standardized images of the pads and bloodstains. Importantly, all images were anonymized; that is, there were no identifying features of the donor in the images. Additionally, each sample was assigned an ID code, which did not link to personal identification information. As shown in Fig.1.

Fig. 1: Simulated Image for the pads

To enhance robustness, a simulated dataset was created using food coloring and gelatin to create realistic viscosity and variations in color. Different volumes of fluid (2-20 ml), gelatin concentrations (5 g, 7.5, and 10 g), and colors (from light red to brown), allowed us to capture a variety of menstrual flow, from light to heavy. During the entire collection process, strict ethical and privacy practices followed. All pads were handled using personal protective equipment, and at the conclusion of the entire process, they were disposed of following biomedical waste practices. Participant anonymity was upheld through not labeling images and submissions with personal identities.

B. Data preprocessing

Before feeding the pad images were introduced to the machine learning algorithm, a number of pre-processing steps were done to sanitize and standardize the data. First, each image was assessed for quality. Any images that were blurry, poorly lit, or contained extraneous objects were dropped. The remaining photographs were centered (cropped or padded) to ensure the sanitary pad was centered with minimal background. All images were converted to one color format (RGB) and reduced to the same dimensions (e.g. 224×224 pixels), to match the input-size requirements of the convolutional neural network. The images were not only sized for the model, but the resizing also standardized the physical size variations in the pads shown in the images. The pixel intensity values were scaled uniformly (i.e., a value in [0,1]) to help ensure a quicker convergence of the model. As shown in Fig.2.

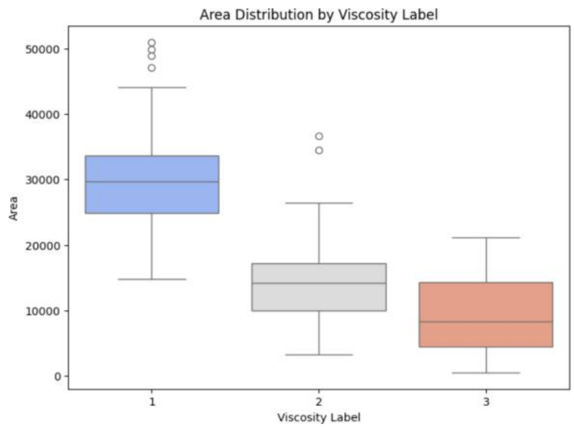

Fig. 2: Analysis of the viscosity label

C. Data Augmentation

To increase the effective dataset size and reduce overfitting, we also employed a variety of image augmentation methods. Since deep learning models require many examples, augmentation is particularly critical because collecting trained photos of menstrual pads is limited and sensitive. We performed the following transformations to randomize training images for each epoch. We added small random rotation (±15°) to account for variation in the pad orientation in pictures. We added horizontal flips (mirroring an image) because the left-right orientation of a pad is not medically meaningful. We avoided vertical flips because the top vs. bottom distribution of blood on the pad may be relevant. Small variations in brightness and contrast were employed to simulate lighting differences and blood stain color vividness. This makes the model somewhat invariant to differences in lighting. Random slight zoom-in/out and shifts were added so the model could learn the rotation, position, and scale of shapes in the image. We added small variations to the blood saturation color. We kept any changes modest because we did not want to distort the intrinsic color characteristics of blood too much, but wanted to make some variations to include the impact of any camera white balance differences.

D. Labels

We formulated a conceptual or practical tripartite scale: Light, Moderate, and Heavy reflecting the amount of blood on the pad. The light category required either direct measurement or visual estimation calibrated against the reference images; for example, if pads were collected physically, the increase in weight of the used pad (compared to a dry pad) gave a volumetric estimate of blood on the pad (1 gram 1mL); those pads with ¡ 20 mL were labeled Light those pads with 20-50 mL were categorized as Moderate and those pads with ¿ 50 mL were categorized as Heavy. This is approximately similar to clinical pictorial chart standards (i.e. with a pad completely soaked with 15mL vs 30mL vs 50+mL of blood). We also categorized the viscosity on each pad as either Low, Medium, or High viscosity. This viscosity classification on the pad was also a subjective, expert visual assessment. Low viscosity blood was indicated by a thin, more uniform stain, which represented watery, or fluid blood with little or no clotting (pad appeared evenly soaked with bright red or light coloured blood); High-viscosity blood was indicated by thickness, and associated qualities of the darkest clot or clotting and lack of uniform distribution of blood may clump rather than be fully absorbed. As shown in Fig.3.

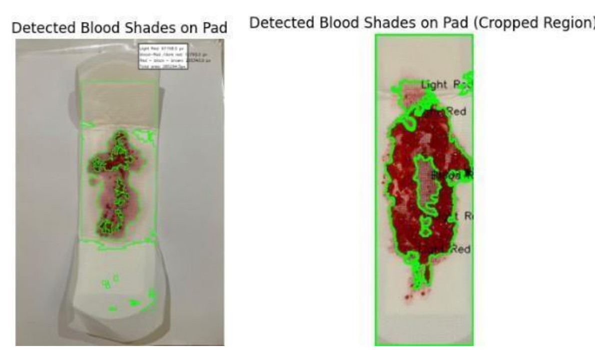

Fig. 3: Sample image with contour marking

E. Model Architecture

Box plots were created using the seaborn and matplotlib libraries to illustrate the distribution and variability in volume, area, and mapped viscosity. These plots offer an advantage in exploring trends and potential outliers in a given dataset. A scatter plot of stained area vs volume colored by viscosity level was also created to visualize clustering and identify anomalies in the dataset. Some of the data points, which contained very extreme volumes or areas (greater than the 95th percentile) were labelled on the plot to denote them as outliers. Image feature extraction was performed using standard computer vision techniques. The stained area determined in each pad image was calculated using contour detection which provided an approximation of total blood flow. Color histograms also gave the pixel intensities for which distributions overserved as approximations to viscosity. Morphological characteristics on things such as the symmetry of the stain and gradients in edge were determined to indicate saturation and spreading behavior. Each image was assigned quantitative scores based on metrics derived from the stained area (A) as a representation of flow volume, average color intensity (C) as a measure of thickness/viscosity and edge sharpness (B) as a measure to represent saturation gradients. The metrics were statistically analyzed for correlation to tagged metadata. Pearson correlation analysis was performed and boxplots and scatter plots were visually inspected for evidence of correlation between flow characteristics and the image features.

We designed a model based on deep-learning applicable to analyzing pad images to predict two outputs (flow level and viscosity) from each image. A convolutional neural network (CNN) architecture was selected as CNNs are well aligned with image recognition problems because they learn spatial features from the pixel data. A transfer learning approach was used to leverage the robust/required model architectures. The backbone for our model was a ResNet-50 CNN, which contains a series of 50 layers of deep residual networks distinguished for performing well in image-classification problems. As represented in Fig.4.

F. Observation

Distinct trends were observed in the processed dataset aligned with the menstrual flow levels. Images labeled with heavy flow showed significantly larger stained areas and higher mean red pixel density, indicating a direct correlation between the stain spread and flow volume. In contrast, images tagged with high viscosity ratings exhibited concentrated, darker cores and sharply defined edges.

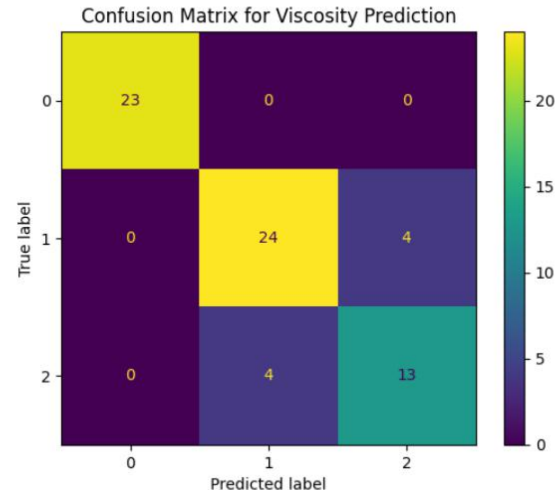

Fig. 4: Confusion matrix for viscosity Prediction

This observation suggests that a higher viscosity results in more localized staining with slower diffusion. In cases of lighter flow, the stains appeared smaller and paler and more diffuse boundaries. Additionally, the saturation pattern in such samples was irregular, suggesting that lower flow and viscosity produce more scattered and unpredictable staining. Overall, the subjective viscosity ratings matched well with the computational metrics derived from the image analysis, providing preliminary validation of the approach. As observed in Fig.5.

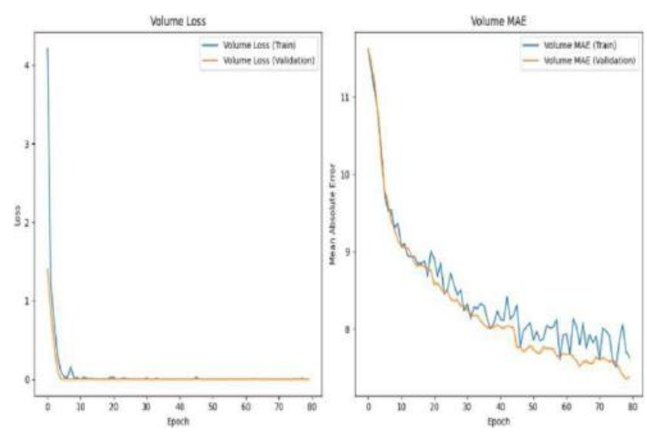

Fig. 5: Roc Curve for Loss

IV RESULT

Statistical analysis revealed strong correlations between image-derived features and manually assigned flow parameters. The stained area showed a Pearson correlation coefficient of approximately 0.82

with flow level, indicating that stain size is a reliable predictor of total discharge volume. Similarly, the average pixel density, used as a proxy for viscosity, correlated at approximately 0.74 with the subjective viscosity scores provided by the participants. A deep learning classifier trained on features such as area, color intensity, and edge sharpness achieved an accuracy of approximately 85% in predicting flow categories. These results validated the feasibility of using low-cost image-based methods to assess key menstrual health indicators with reasonable accuracy. As displayed on Fig.6.

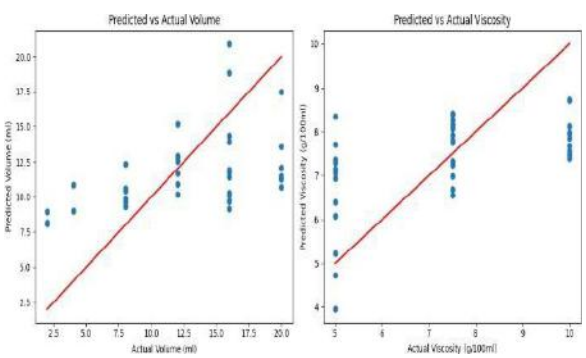

Fig. 6: Results

V DISCUSSION

Unlike the Pictorial Blood Loss Assessment Chart whose accuracy depends on patient recall and subjective stain shading, the proposed image analysis provides an objective, reproducible metric in real time. weighed-pad method eliminates the need for calibrated laboratory scales and immediate pad sealing, reducing workflow burden. Clinically, nurses could deploy the app during telehealth consultations to triage patients reporting acute heavy bleeding, guiding immediate referral versus conservative management. In outpatient settings, hematology services might offer the tool for weekly home monitoring of iron-deficiency patients Next-phase work should explore multimodal learning that fuses pad images with signals already collected by consumer wearables—skin temperature, heart-rate variability, and galvanic response—to refine the phase prediction and bleed-volume inference. Generative augmentation (e.g., diffusion-based stain synthesis) can mitigate class imbalance, whereas federated training allows models to learn from geographically dispersed clinics without exporting sensitive images.

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