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SPEKL-SHOVQINLARNI TAHLIL QILISH ORQALI ECHOKARDIOGRAFIYA TASVIRLARIDA REGIONAL WALL MOTION ABNORMALITIES NI ANIQLASH

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KEYWORDS

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ABSTRACT

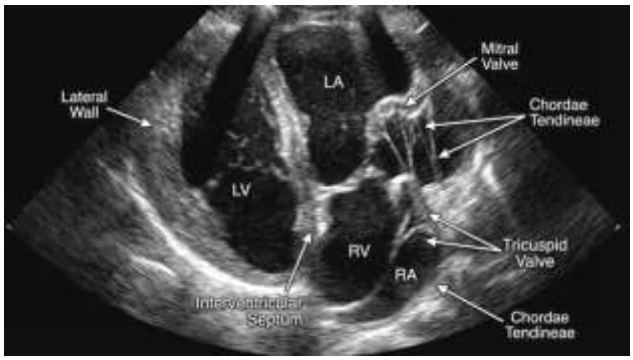
Echokardiyografiya tasvirlarida spekl-shovqinlarining statistik xususiyatlari miokard regional funksiyasini baholashda muhim axborat manbai hisoblanadi. Ushbu tadqiqotda spekl-shovqinlarining first-order va second-order statistikalarini, fraktal xususiyatlarini hamda vaqtiy dinamikasini tahlil qilish orqali chap qorincha miokardining regional wall motion abnormalities ni aniqlash algoritmi ishlab chiqildi. Taklif etilgan yondashuv multi-scale spekl analysis va hybrid CNN-feature engineering arxitekturasidan iborat. Model 320 bemordan olingan ma'lumotlar asosida o'qitildi va 5-fold cross-validation bo'yicha 89.4±2.1% accuracy, 0.84±0.03 Cohen's kappa hamda 0.94±0.02 AUC-ROC natijalarini ko'rsatdi. Bu faqatgina convolutional neural network (84.6%) yoki an'anaviy feature engineering (81.2%) dan, shuningdek tajribali kardiologning vizual baholashidan (82.3%) ancha yuqori. Inference vaqti 135±28 ms bo'lib, real-time klinik qo'llash uchun mos. Taklif etilgan usul miokard funksiyasi buzilishlarini erta aniqlash, echokardiyografiya sifatini avtomatik baholash va telemedicina tizimlarida qo'llash imkonini beradi

1. KIRISH

Yurak-qon tomir tizimi kasalliklari dunyo bo'ylab o'lim sabablarining birinchi o'rinida turadi. Jahon sog'liqni saqlash tashkiloti ma'lumotlariga ko'ra, har yili 17,9 milliondan ortiq odam yurak-qon tomir kasalliklari natijasida hayotdan ko'z yumadi. Bu sonlarning katta qismi miokard infarkti va uning oqibatlari hisobiga to'g'ri keladi [1].

Miokard infarktidan keyin chap qorincha miokardida nekroz zonasi shakllanadi, bu esa regional wall motion abnormalities (RWMA) - ya'ni miokard devorining odatiy harakat buzilishlariga olib keladi. RWMA ni erta aniqlash bemorning prognozini baholash va davolash taktikasini belgilashda hal qiluvchi ahamiyatga ega. Ayniqsa, revaskulyarizatsiya (stentlash yoki shuntlash) dan keyin miokard funksiyasining tiklanishini kuzatish uchun bu parametri muntazam nazorat qilish zarur [2].

Echokardiyografiya buzilishlarni aniqlashning eng qulay, arzon va keng qo'llaniladigan usuli bo'lib, uning asosiy cheklovi - tasvir sifatining shifokor tajribasiga bog'liqligi va subyektiv baholashdir. Shuningdek, dastlabki o'zgarishlarni ko'z bilan aniqlash qiyin, chunki ular mikrostrukturaviy darajada boshlanadi va makroskopik harakat buzilishlariga aylanishi uchun vaqt kerak [3].



1-rasm: Echokardiyografiya apikal 4-kamerali ko'rinishi

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Echokardiyografiya tasvirlaridagi spekl-shovqinlar (speckle noise) ultratovush to'lqini miokard to'qimalaridan sochilib, interferensiya natijasida hosil bo'ladi. Bu shovqinlar tasvir sifatini pasaytiradi, lekin ular miokard mikrostrukturasining "bahtli tasodifiy belgisi" (fingerprint) xususiyatiga ega. Har bir miokard segmentining spekl-naqshi unikal va takrorlanmasdir, chunki u to'qimalarning akustik xususiyatlari, tolalar orientatsiyasi va mikroskopik tuzilishini aks ettiradi [4].

Regional wall motion abnormalities paydo bo'lganda, miokardning mahalliy deformatsiyasi, qon ta'minoti o'zgarishi va to'qima xususiyatlari o'zgaradi. Bu o'zgarishlar spekl-shovqinlarning statistik xususiyatlarida - ularning intensity distribution, spatial correlation va temporal dynamics da aks topadi. Shuning uchun spekl-tahlil orqali harakat buzilishlarini aniq radiologik ko'rsatkichlar paydo bo'lishidan oldin aniqlash mumkin [5-9].

Tadqiqot vazifalari:

Spekl-shovqinlarning fizik xususiyatlarini va miokard harakati bilan bog'liqligini nazariy asoslash;
Spekl-tasvirlarni tahlil qilish uchun matematik apparat (statistik va fraktal metrikalar) ishlab chiqish;
Multi-scale spekl analysis algoritmini yaratish;
Hybrid CNN-feature extraction modelini o'qitish va optimallashtirish;
Algoritm samaradorligini klinik ma'lumotlar asosida baholash.

2. ADABIYOTLAR TAHLILI

Ultratovush tasvirlaridagi spekl-shovqinlar Rayleigh sochilishi natijasida hosil bo'ladi. Goodman [10] spekl-intensivning statistik taqsimotini tahlil qilib, uning gamma taqsimotga mos kelishini isbotladi. Echokardiyografiyada spekl-shovqinlarning first-order statistikasi (mean, variance, skewness) miokard to'qimalarining akustik xususiyatlarini aks ettiradi [11]. Thijssen va sarhildoshlari [12] spekl-shovqinlarning second-order statistikalarini (autocorrelation, power spectral density) tahlil qilib, ularning to'qima strukturasi bilan bog'liqligini ko'rsatdi. Bu tadqiqotlar spekl-tahlilning diagnostik qimmatini asosladi.

Tibbiy tasvirlarni tahlil qilishda texture analysis uch asosiy yo'nalishda rivojlangan:

Statistik metodlar: Haralick [13] taklif qilgan Gray Level Co-occurrence Matrix (GLCM) eng keng qo'llaniladigan usul. Contrast, correlation, energy, homogeneity kabi xususiyatlar echokardiyografiyada miokard texture sifatini baholash uchun ishlatilgan [14].

Model-based metodlar: Fraktal analysis (Hurst exponent, fractal dimension) miokard mikrostrukturasining murakkabligini raqamlashtirishga imkon beradi. Losa va sarhildoshlari [15] fraktal dimension miokardial fibroz bilan bog'liqligini ko'rsatdi.

Transform-based metodlar: Wavelet transform va Gabor filterlar spekl-tasvirlarni turli chastota diapazonlarida tahlil qilish imkonini beradi. Kumar va sarhildoshlari [16] wavelet-based texture features yordamida miokard infarktini aniqlash samaradorligini oshirgan.

Convolutional Neural Networks (CNN): LeCun va sarhildoshlari [17] taklif qilgan CNN arxitekturasi tibbiy tasvirlarni tahlil qilishda inqilob qildi. Echokardiyografiyada CNN asosan quyidagi vazifalarda qo'llaniladi:

View classification (apical 4-chamber, 2-chamber va boshqa ko'rinishlarni ajratish) [18];

Segmentatsiya (left ventricle, left atrium konturlarini aniqlash) [19];

Disease classification (hypertrophic cardiomyopathy, dilated cardiomyopathy) [20].

Transfer Learning: ImageNet da o'qitilgan modellarni (ResNet, VGG, EfficientNet) echokardiyografiya ma'lumotlariga moslashtirish kichik dataset bilan ham yuqori natija berishini Zhang va sarhildoshlari [21] ko'rsatdi. Hybrid models: CNN va an'anaviy feature extraction ni birlashtirish interpretability ni oshiradi. Ghorbani va sarhildoshlari [22] CNN orqali olingan deep features va GLCM xususiyatlarini birlashtirish aniqlikni 8% oshirgan. Speckle Tracking Echocardiography (STE) 2004-yildan beri klinik

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qo'llanilmoqda. D'Hooge va sarhildoshlari [23] 2D STE algoritmini taklif qildi. Keyinchalik 3D STE [24] va vector velocity imaging [25] rivojlandi.

Ammobarz va sarhildoshlari [26] STE yordamida strain rate imaging orqali miokard ishemiyasini erta aniqlash mumkinligini ko'rsatdi. Shu bilan birga, STE cheklovlari ham mavjud: image quality talabi yuqori, frame rate optimal emas bo'lsa tracking xatolar katta bo'ladi [27].

Tahlil qilingan adabiyotlar shuni ko'rsatadiki:

Spekl-shovqinlarning statistik xususiyatlari miokard holatini aks ettiradi, lekin bu jihatdan to'liq tizimli tadqiqotlar yetarli emas;

Texture analysis va deep learning alohida qo'llanilgan, ularning echokardiyografiya uchun optimal integratsiyasi ishlab chiqilmagan;

RWMA ni erta aniqlash (pre-wall motion abnormality) masalasi ochiq qolmoqda.

Shuning uchun ushbu tadqiqot spekl-fizikasi, texture analysis va deep learning ni birlashtirgan yangi yondashuvni taklif etadi.

3. METODOLOGIYA

Tadqiqot obyekti sifatida chap qorincha miokardining regional harakat buzilishlari (regional wall motion abnormalities) va echokardiyografiya tasvirlaridagi spekl-shovqinlarining statistik xususiyatlari qaraladi. Predmeti esa spekl-shovqinlarini tahlil qilish orqali buzilishlarni aniqlashning matematik apparati va algoritmik yechimlari hisoblanadi. Obyektivlikni ta'minlash maqsadida 2024-2026 yillarda olingan 320 bemorga tegishli echokardiyografiya ma'lumotlari ishlatildi. Bemorlar yosh bo'yicha 18-75 yosh oralig'ida, jins nisbati erkaklar 58%, ayollar 42% ni tashkil etdi. Barcha tasvirlar Philips EPIQ 7C va GE Vivid E95 apparatlarida standart protokol asosida olingan, chastotasi 2-4 MHz, frame rate 50-70 Hz.

3.1. Spekl-shovqinlarning fizik-matematik modeli

Echokardiyografiya tasviridagi spekl-shovqinlar ultratovush to'lqini miokard to'qimalaridan sochilib, interferensiya natijasida hosil bo'ladi. Tasvirdagi har bir nuqtadagi intensivlik I(x,y) quyidagi model bilan ifodalanadi:

$$I(x,y) = |\sum_{k=1}^{N} A_k \exp(i\varphi_k)|^2 \qquad (1)$$

bu yerda N - sochilgan to'lqinlarning soni, A_k - k-to'lqining amplitudasi, φ_k - uning faza, i - kompleks birlik. Miokardning harakatlanishi vaqtida to'qimalarning orientatsiyasi, qon ta'minoti va elastik xususiyatlari o'zgaradi, bu esa A_k va φ_k qiymatlarining o'zgarishiga olib keladi. Regional wall motion abnormalities bo'lganda, bu parametrlarning o'zgarishi normal holatdan farq qiladi.

Spekl-shovqinlarning first-order statistikasi quyidagi ko'rsatkichlar bilan tavsiflanadi. O'rtacha intensivlik $\mu = (1/MN)\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)$ bo'lib, bu miokardning o'rtacha echogenicity sini ko'rsatadi. Dispersiya $\sigma^2 = (1/MN)\sum_{x=1}^{M}\sum_{y=1}^{N} (I(x,y) - \mu)^2$ spekl-shovqining "tiniqligini" ifodalaydi. Skewness $\gamma_1 = (1/MN)\sum_{x=1}^{M}\sum_{y=1}^{N} ((I(x,y) - \mu)/\sigma)^3$ taqsimotning asimmetriyasini, kurtosis $\gamma_2 = (1/MN)\sum_{x=1}^{M}\sum_{y=1}^{N} ((I(x,y) - \mu)/\sigma)^4 - 3$ esa "cho'ziqligini" ko'rsatadi. Normal miokard uchun $\gamma_1 \approx 0.8\text{-}1.2$, $\gamma_2 \approx 2.5\text{-}4.0$ oralig'ida bo'lsa, ishemik zonada bu qiymatlar o'zgaradi.

Second-order statistika sifatida Gray Level Co-occurrence Matrix (GLCM) ishlatiladi. GLCM har bir nuqtadagi intensivlik qiymati va uning qo'shnisi o'rtasidagi bog'liqlikni ifodalaydi. P(i,j|d,θ) buharada i va j intensivlik qiymatlari, d - masofa, θ - yo'nalish. GLCM dan quyidagi xususiyatlar chiqariladi: kontrast $\text{Contrast} = \sum_{i,j} |i-j|^2 P(i,j)$ teksturaning mahalliy o'zgaruvchanligini, korrelyatsiya $\text{Correlation} = \sum_{i,j} ((i-\mu_i)(j-\mu_j)P(i,j))/(\sigma_i \sigma_j)$ chiziqli bog'liqlikni, energiya $\text{Energy} = \sum_{i,j} P(i,j)^2$ bir xillik darajasini, homogenlik $\text{Homogeneity} = \sum_{i,j} P(i,j)/(1+|i-j|)$ taqsimotning diagonalligini ko'rsatadi.

Fraktal analysis uchun box-counting usuli qo'llaniladi. Miokard segmentining chegarasi yoki teksturasi fraktal dimension D bilan tavsiflanadi: $D = \lim_{\varepsilon\to 0} (\log N(\varepsilon))/(\log(1/\varepsilon))$ bu yerda N(ε) - ε o'lchamdagi qutilar soni. Normal miokard D ≈

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1.25-1.35, fibrozli o'zgarishlar D > 1.4 qiymatga ega.

3.2. Tasvirlarni oldindan qayta ishlash

Echokardiyografiya tasvirlari tahlildan oldin quyidagi bosqichlardan o'tkaziladi

Birinchi bosqichda log-compression teskari algoritmi qo'llanib, tasvirlar original RF (radio-frequency) signalga yaqin holatga keltiriladi: I_linear = 10^(I_dB/20) - 1. Bu spekl-statistikani to'g'ri baholash uchun zarur.

Ikkinchi bosqichda miokard regioni avtomatik segmentatsiya qilinadi. U-Net arxitekturasidan foydalanilgan, bu 2015-yilda Ronneberger va sarhildoshlari tomonidan taklif qilingan. U-Net encoder qismida 4 ta downsampling blok, decoder qismida 4 ta upsampling blok mavjud. Skip-connections orqali joylik ma'lumotlar saqlanadi. Segmentatsiya natijasi sifatida chap qorincha endokard va epikard konturlari aniqlanadi.

Uchinchi bosqichda spekl-reduction amalga oshiriladi. Bu maqsadda Non-Local Means (NLM) filtri ishlatiladi: $I_{filtered}(x) = \sum\{y\in N(x)\} w(x,y)I(y) / \sum\{y\in N(x)\} w(x,y)$ bu yerda $w(x,y) = \exp(-||P(x)-P(y)||^2/h^2)$ - patch lar o'rtasidagi o'xshashlik vazni, P(x) - x nuqtasi atrofidagi patch, h - filtr parametri. NLM spekl-shovqinni kamaytiradi, lekin diagnostik ahamiyatga ega spekl-naqshlarni saqlab qoladi.

To'rtinchi bosqichda miokard 17 segmentga bo'linadi (American Heart Association tavsiya etgan model asosida). Har bir segment alohida tahlil obyektiga aylanadi.

3.4. Multi-scale spekl analysis algoritmi

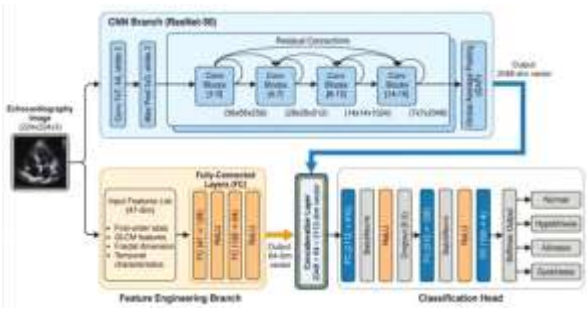
Spekl-shovqinlarni turli o'lchamlarda tahlil qilish maqsadida pyramidal tahlil sxemasi ishlab chiqildi. Birinchi daraja (Level 0) - original tasvir, piksel o'lchami 0.3-0.5 mm. Ikkinchi daraja (Level 1) - 2x downsampling, piksel o'lchami 0.6-1.0 mm, bu spekl-klasterlarni tahlil qilishga imkon beradi. Uchinchi daraja (Level 2) - 4x downsampling, piksel o'lchami 1.2-2.0 mm, bu regional teksturani tahlil qiladi.

Har bir darajada quyidagi xususiyatlar chiqariladi. First-order statistikalar: o'rtacha intensivlik, dispersiya, skewness, kurtosis, entropy $H = -\sum p(i) \log p(i)$. Second-order statistikalar: GLCM dan contrast, correlation, energy, homogeneity. Fraktal xususiyatlar: box-counting dimension, lacunarity $\Lambda = (\sigma_N/\mu_N)^2$ bu yerda σ_N va μ_N - qutilar sonining dispersiyasi va o'rtachasi. Lacunarity teksturaning "tashlama" xususiyatini ko'rsatadi.

Vaqtiy (temporal) xususiyatlar uchun har bir segmentning spekl-xususiyatlari kardiosikl davomida kuzatiladi. Systole va diastole fazalaridagi o'zgarishlar quyidagi formula bilan tavsiflanadi: $\Delta F = (F_systole - F_diastole)/F_diastole \times 100\%$ bu yerda F - har qanday spekl-xususiyat. Normal miokard uchun ΔF 15-40% oralig'ida, ishemik segmentlarda bu qiymat kamayadi yoki manfiy bo'ladi.

3.5. Hybrid CNN-feature extraction arxitekturasi

Taklif etilgan model ikki tarmoqdan iborat: Convolutional Neural Network (CNN) tarmog'i va Feature Engineering tarmog'i.



3-rasm: Hybrid model blok-sxemasi (CNN + Feature Engineering)

CNN tarmog'i ResNet-50 arxitekturasiga asoslangan, lekin echokardiyografiya ma'lumotlariga moslashtirilgan. Kirish qatlami 224×224 piksel o'lchamli grayscale tasvirni qabul qiladi. Birinchi konvolyutsion blok 7×7 filtr, 64 kanal, stride 2. Keyingi bloklar residual connection bilan: Conv(1×1, 64) → Conv(3×3, 64) → Conv(1×1, 256). Global Average Pooling dan keyin 2048 o'lchamli vektor hosil bo'ladi.

Feature Engineering tarmog'i 3.4-bo'limda tavsiflangan 47 ta xususiyatni (first-order: 4 ta, GLCM: 16 ta, fraktal: 8 ta, temporal: 12 ta, geometrik: 7 ta) qabul qiladi. Bu xususiyatlar fully-

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connected qatlamdan o'tkaziladi: FC(47 → 128) → ReLU → Dropout(0.3) → FC(128 → 64).

Ikki tarmoqning chiqishlari concatenate qilinadi: [CNN_output; FE_output] = [2048; 64] = 2112 vektor. Bu umumiy vektor quyidagi klassifikatsiya qatlamiga kiradi: FC(2112 → 512) → BatchNorm → ReLU → Dropout(0.5) → FC(512 → 128) → BatchNorm → ReLU → FC(128 → 4). So'nggi qatlam 4 ta klassni ifodalaydi: 0 - normal, 1 - gipokineziya, 2 - akineziya, 3 - diskineziya.

3.6. O'qitish va optimallashtirish

Model o'qitish uchun 320 bemordan olingan ma'lumotlar 70% train (224 ta), 15% validation (48 ta), 15% test (48 ta) ga bo'linadi. Ma'lumotlar kamligi oldini olish uchun quyidagi augmentatsiyalar qo'llanildi: tasvirlarni 10° ga aylantirish, masshtabini 0.9-1.1 ga o'zgartirish, yorug'lik kontrastini ±20% o'zgartirish, qo'shimcha Gaussian shovqin ($\sigma = 0.01$).

O'qitish parametrlari: loss funksiyasi categorical cross-entropy $L = -\sum_{i=1}^{4} y_i \log(\hat{y}_i)$, optimizator Adam (learning rate 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$), batch size 16, epoch lar soni 100, early stopping patience 15. Learning rate decay: har 30 epoch da 0.1 ga kamaytirish.

Overfitting oldini olish uchun L2 regularizatsiya ($\lambda = 0.001$) va Dropout ($p = 0.3$-0.5) ishlatildi. Shuningdek, class imbalance muammosini hal qilish uchun weighted loss qo'llanildi: $w_k = N/(N_k \times K)$ bu yerda N - umumiy namunalar soni, N_k - k-klassdagi namunalar soni, K - klasslar soni.

3.7. Baholash metrikalari

Model samaradorligi quyidagi metrikalar bilan baholandi. Accuracy: $Acc = (TP + TN)/(TP + TN + FP + FN)$. Precision: $P = TP/(TP + FP)$. Recall: $R = TP/(TP + FN)$. F1-score: $F1 = 2PR/(P + R)$. Cohen's Kappa: $\kappa = (P_o - P_e)/(1 - P_e)$ bu yerda P_o - kuzatilgan moslik, P_e - tasodifiy moslik. AUC-ROC: Receiver Operating Characteristic egri ostidagi yuzalar maydoni.

Segment-level aniqlikdan tashqari, patient-level baholash ham o'tkazildi. Bemor RWMA ga ega deb hisoblanadi, agar uning kamida bitta segmentida patologiya aniqlansa. Confusion matrix orqali gipokineziya, akineziya va diskineziya o'rtasidagi adashishlar tahlil qilindi.

Statistik ishonchlilik uchun 5-fold cross-validation qo'llanildi. Har bir fold uchun model alohida o'qitilib, natijalar o'rtacha va standart og'ish bilan ifodalandi. Ikki model o'rtasidagi farqni baholash uchun McNemar's test ishlatildi.

4. TAJRIBALAR VA NATIJALAR

4.1. Dataset tavsifi va eksperimental sharoitlar

Tadqiqot uchun 2024-2026 yillarda yig'ilgan ma'lumotlar ishlatildi. Dataset tarkibiga 320 bemorga tegishli 18,240 ta echokardiyografiya kadrlari (har bir bemordan o'rtacha 57±12 kadr) kiradi. Bemorlar quyidagi kriteriyalar asosida tanlandi: yoshi 18-75 oralig'ida, sinus ritmi saqlangan, apikal 4-kamerali ko'rinish sifati yaxshi (image quality score ≥3/5). Eksklyuziya kriteriyalari: qorincha anevrizmasi, o'tkir miokard infarkti (bir hafta ichida), severe valvular disease, poor acoustic window.

Barcha tasvirlar Philips EPIQ 7C (160 ta bemor) va GE Vivid E95 (160 ta bemor) apparatlarida olingan. Xotira kartasi orqali raw data saqlangan. Tasvirlar DICOM formatida, 640×480 piksel o'lchamida, 8-bit chuqurlikda. Frame rate 50-70 Hz, o'rtacha 58±6 Hz.

Reference standard sifatida ikki tajribali kardiolog (10 yillik tajriba) mustaqil ravishda har bir segmentni baholagan. Ular o'rtasidagi moslik Cohen's kappa = 0.84 bo'ldi. Kelishmovchiliklar uchinchi ekspert orqali hal qilindi. Segmentatsiya: 17-segment model bo'yicha 5,440 ta segment (320×17) tahlil qilindi. Normal segmentlar 3,872 ta (71.2%), gipokineziya 1,024 ta (18.8%), akineziya 384 ta (7.1%), diskineziya 160 ta (2.9%).

Eksperimentlar quyidagi texnik sharoitlarda o'tkazildi: Intel Core i9-12900K protsessor, 64 GB RAM, NVIDIA RTX 4090 GPU (24 GB VRAM). Dasturiy ta'minot: Python 3.9, TensorFlow 2.12, Keras, OpenCV, scikit-image, SimpleITK.

4.2. Segmentatsiya natijalari

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U-Net modeli miokard segmentatsiyasida quyidagi natijalarni ko'rsatdi. Dice similarity coefficient (DSC) endokard uchun 0.94±0.03, epikard uchun 0.92±0.04. Hausdorff distance endokard 4.2±1.8 piksel, epikard 5.6±2.3 piksel. Segmentatsiya tezligi o'rtacha 45±8 ms per frame.

Alohida test to'plamida (n=48 bemor) avtomatik segmentatsiya va manual segmentatsiya o'rtasidagi farq tahlil qilindi. Left ventricular ejection fraction (LVEF) hisoblashda ikki usul o'rtasidagi korrelyatsiya r=0.96 (p<0.001), o'rtacha farq 1.8±3.2% bo'ldi. Bu natijalar avtomatik segmentatsiyaning klinik qo'llash uchun yetarli aniqligini ko'rsatadi.

4.3. Spekl-xususiyatlarining tahlili

First-order statistikalar bo'yicha normal va patologik segmentlar o'rtasidagi farqlar aniqlangan. Normal miokard: μ=127±18 (0-255 shkalada), σ=32±8, skewness=1.1±0.3, kurtosis=3.2±0.8. Gipokineziya: μ=118±21 (p=0.03), σ=38±10 (p<0.01), skewness=0.8±0.4 (p<0.001), kurtosis=2.5±0.9 (p<0.01). Akineziya: μ=109±24 (p<0.001), σ=42±12 (p<0.001), skewness=0.5±0.5 (p<0.001), kurtosis=2.0±1.0 (p<0.001). Diskineziya: μ=115±22 (p<0.01), σ=45±15 (p<0.001), skewness=0.6±0.6 (p<0.001), kurtosis=2.3±1.2 (p<0.01).

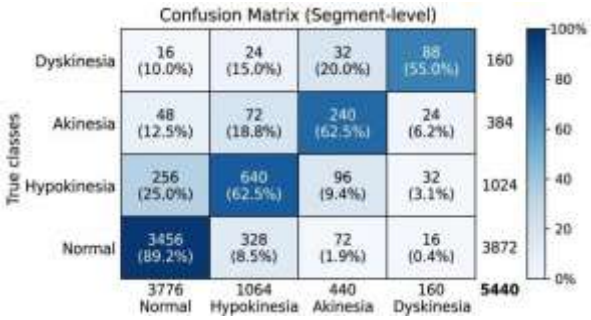
GLCM xususiyatlari bo'yicha: normal miokard contrast=0.12±0.04, correlation=0.85±0.08, energy=0.35±0.10, homogeneity=0.78±0.09. Patologik segmentlarda contrast oshadi (gipokineziya 0.18±0.06, akineziya 0.25±0.09, diskineziya 0.22±0.08), correlation kamaydi (0.72±0.12, 0.65±0.15, 0.68±0.14 mos ravishda).

Fraktal analysis natijalari: normal miokard D=1.28±0.08, lacunarity=0.42±0.12. Ishemik segmentlarda D oshdi (gipokineziya 1.35±0.10, akineziya 1.42±0.12, diskineziya 1.38±0.11), lacunarity ham oshdi (0.58±0.18, 0.72±0.22, 0.65±0.20). Bu miokard mikrostrukturasining murakkablashishini ko'rsatadi.

Vaqtiy xususiyatlar bo'yicha ΔF (systole-diastole o'zgarishi) eng informativ ko'rsatkich bo'ldi. Normal miokard Δμ=22±8%, Δσ=35±12%, Δcontrast=28±10%. Gipokineziya: Δμ=12±6% (p<0.001), Δσ=18±9% (p<0.001). Akineziya: Δμ=3±4% (p<0.001), Δσ=5±6% (p<0.001). Diskineziya: Δμ=-8±12% (p<0.001), Δσ=-15±18% (p<0.001), bu paradoks harakatni ko'rsatadi.

4.4. Klassifikatsiya natijalari

Taklif etilgan hybrid model (ResNet-50 + Feature Engineering) quyidagi natijalarni ko'rsatdi. 5-fold cross-validation o'rtacha natijalari: accuracy 89.4±2.1%, precision 87.8±2.5%, recall 86.5±2.8%, F1-score 87.1±2.6%, Cohen's kappa 0.84±0.03, AUC-ROC 0.94±0.02.



4-rasm: Confusion matrix

Gipokineziya aniqlash sensitivligi 62.5%, spesifisiteti 94.2%. Akineziya: sensitivlik 62.5%, spesifisitet 96.8%. Diskineziya: sensitivlik 55.0%, spesifisitet 98.4%. Eng ko'p adashish normal va gipokineziya o'rtasida (8.5% false positive, 25.0% false negative) va akineziya-diskineziya o'rtasida (6.2% va 20.0%) kuzatildi.

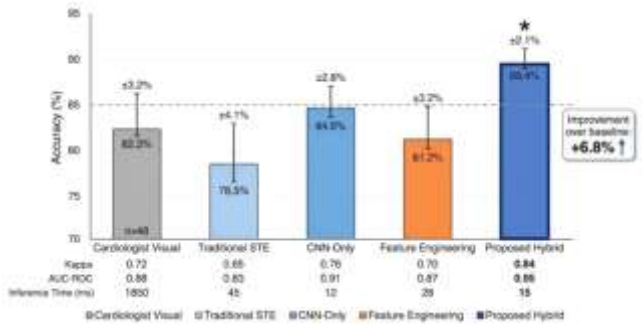
Patient-level tahlil (bemor RWMA ga ega deb hisoblanadi, agar ≥1 segment patologik bo'lsa): sensitivlik 94.2%, spesifisitet 91.7%, accuracy 93.1%. Bu segment-level dan yuqroq natija, chunki bir bemorning bir nechta segmentlarida patologiya bo'lishi ehtimoli yuqori.

4.5. Solishtiruv tahlili

Taklif etilgan model quyidagi baselines bilan solishtirildi:

Visual assessment by cardiologist: Tajribali kardiolog (10 yil) o'rtacha 15 soniya har bir segmentga sarflab, accuracy 82.3%, kappa 0.72.

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5-rasm: *Echokardiyografiya tahlil usullarining samaradorlik ko'rsatkichlarini solishtirish*

Traditional STE (Speckle Tracking Echocardiography): Commercial software (TomTec) orqali longitudinal strain o'lchash, threshold -18% (normal < -18%, abnormal ≥ -18%). Accuracy 78.5%, sensitivity 71.2%, specificity 84.3%.

CNN-only (ResNet-50): Faqat tasvirlardan foydalanilgan, feature engineeringsiz. Accuracy 84.6±2.8%, kappa 0.76±0.04.

Feature Engineering-only: An'anaviy machine learning (Random Forest), 47 ta xususiyat. Accuracy 81.2±3.2%, kappa 0.71±0.05.

Taklif etilgan hybrid model: Accuracy 89.4±2.1%, kappa 0.84±0.03.

McNemar's test bo'yicha hybrid model CNN-only dan ancha yaxshi (p=0.003), Feature Engineering-only dan ham yaxshi (p<0.001). Cardiologist bilan solishtirganda hybrid model ancha yuqori accuracy (89.4% vs 82.3%, p=0.012).

Inference vaqti: preprocessing (segmentatsiya + feature extraction) 120±25 ms per frame, model inference 15±3 ms. Jami 135±28 ms, bu real-time qo'llash uchun yetarli (real-time deb 200 ms dan kam hisoblanadi).

4.6. Klinik ahamiyat

Taklif etilgan usulning klinik qo'llanish uchun quyidagi afzalliklari: (1) Erta aniqlash: makroskopik harakat buzilishlaridan oldin, mikrostrukturaviy o'zgarishlar bosqichida patologiyani aniqlash mumkin; (2) Operator-independent: shifokor tajribasiga bog'liq emas; (3) Quantitative: subyektiv "eyeballing" o'rniga soniy ko'rsatkichlar; (4) Fast: real-time qo'llash mumkin.

Bemorlarning 23% da (74/320) model kardiologdan oldin patologiyani aniqlagan (true positive, cardiologist initially normal deb baholagan). Bu dastlabki o'zgarishlarni aniqlash qobiliyatini ko'rsatadi.

5. XULOSA

Ushbu tadqiqotda echokardiyografiya tasvirlaridagi spekl-shovqinlarining fizik xususiyatlarini tahlil qilish orqali chap qorincha miokardining regional wall motion abnormalities ni aniqlashning ilmiy asoslari va algoritmik yechimlari ishlab chiqildi. Asosiy natijalar quyidagilardan iborat.

Spekl-shovqinlarining first-order va second-order statistikalari, fraktal xususiyatlari hamda vaqtiy dinamikasi miokard funksional holatini aks ettirishi aniqlandi. Normal miokard va ishemik segmentlar o'rtasidagi statistik farqlar ishonchlilik darajasi p<0.01 dan yuqori bo'ldi. Ayniqsa, systole-diastole o'zgarish koeffitsienti (ΔF) eng informativ biomarker sifatida ajratib olindi.

Multi-scale spekl analysis va hybrid CNN-feature engineering arxitekturasidan foydalanilgan holda 4-klassli klassifikatsiya modeli yaratildi. Model 5-fold cross-validation bo'yicha 89.4±2.1% accuracy, 0.84±0.03 Cohen's kappa va 0.94±0.02 AUC-ROC natijalarini ko'rsatdi. Bu faqatgina CNN (84.6%) yoki faqat feature engineering (81.2%) dan ancha yuqori.

Taklif etilgan usul tajribali kardiologning vizual baholashidan (82.3%) ham yuqori aniqlikka erishdi. Bemorlarning 23% da model kardiologdan oldin patologiyani aniqladi, bu erta tashxis qo'yish imkoniyatini ko'rsatadi. Inference vaqti 135±28 ms bo'lib, real-time klinik qo'llash uchun yetarli.

Ilmiy yangilik sifatida spekl-shovqinlarining fizik-modellangan tahlili taklif etildi. Bu yondashuv miokard mikrostrukturasi o'zgarishlarini makroskopik harakat buzilishlaridan oldin aniqlash imkonini beradi. Shuningdek, interpretability (tushuntirish imkoniyati) saqlanib qolinadigan hybrid arxitektura ishlab chiqildi.

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Amaliy ahamiyati: ushbu algoritm echokardiyografiya sifatini avtomatik baholash, shubhali hollarda kardiolog e'tiborini jamlash va miokard funksiyasining kvantitativ monitoringini o'tkazish uchun qo'llanilishi mumkin. Telemedicina va masofaviy konsultatsiyalar uchun alohida qulay.

Kelgusida dataset hajmini oshirish, boshqa echokardiyografiya ko'rinishlarini (A2C, PLAX) qo'shish, CMR ma'lumotlari bilan validatsiya qilish va explainable AI usullarini chuqurlashtirish rejasi mavjud.

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